# autogluon_each_location

October 18, 2023

[1]:
```
# config

label = 'y'
metric = 'mean_absolute_error'
time_limit = 60*30
presets = 'best_quality'

do_drop_ds = True
# hour, dayofweek, dayofmonth, month, year
use_dt_attrs = ["hour", "year"]
use_estimated_diff_attr = False
use_is_estimated_attr = True

use_groups = False
n_groups = 8

auto_stack = False
num_stack_levels = 0
num_bag_folds = 8
num_bag_sets = 20

use_tune_data = True
use_test_data = True
tune_and_test_length = 0.5 # 3 months from end
holdout_frac = None
use_bag_holdout = True # Enable this if there is a large gap between score_val␣
↪and score_test in stack models.

sample_weight = None#'sample_weight' #None
weight_evaluation = False
sample_weight_estimated = 1

run_analysis = True
```

[2]:
```
import pandas as pd
import numpy as np
```

```python
import warnings
warnings.filterwarnings("ignore")


def feature_engineering(X):
    # shift all columns with "1h" in them by 1 hour, so that for index 16:00, we have the values from 17:00
    # but only for the columns with "1h" in the name
    #X_shifted = X.filter(regex="\dh").shift(-1, axis=1)
    #print(f"Number of columns with 1h in name: {X_shifted.columns}")


    columns = ['clear_sky_energy_1h:J', 'diffuse_rad_1h:J', 'direct_rad_1h:J',
       'fresh_snow_12h:cm', 'fresh_snow_1h:cm', 'fresh_snow_24h:cm',
       'fresh_snow_3h:cm', 'fresh_snow_6h:cm']

    X_shifted = X[X.index.minute==0][columns].copy()
    # loop through all rows and check if index + 1 hour is in the index, if so get that value, else nan
    count1 = 0
    count2 = 0
    for i in range(len(X_shifted)):
        if X_shifted.index[i] + pd.Timedelta('1 hour') in X.index:
            count1 += 1
            X_shifted.iloc[i] = X.loc[X_shifted.index[i] + pd.Timedelta('1 hour')][columns]
        else:
            count2 += 1
            X_shifted.iloc[i] = np.nan

    print("COUNT1", count1)
    print("COUNT2", count2)

    X_old_unshifted = X[X.index.minute==0][columns]
    # rename X_old_unshifted columns to have _not_shifted at the end
    X_old_unshifted.columns = [f"{col}_not_shifted" for col in X_old_unshifted.columns]

    # put the shifted columns back into the original dataframe
    #X[columns] = X_shifted[columns]



    date_calc = None
    if "date_calc" in X.columns:
```

```
        date_calc = X[X.index.minute == 0]['date_calc']

    # resample to hourly
    print("index: ", X.index[0])
    X = X.resample('H').mean()
    print("index AFTER: ", X.index[0])

    X[columns] = X_shifted[columns]
    #X[X_old_unshifted.columns] = X_old_unshifted

    if date_calc is not None:
        X['date_calc'] = date_calc

    return X




def fix_X(X, name):
    # Convert 'date_forecast' to datetime format and replace original column␣
↪with 'ds'
    X['ds'] = pd.to_datetime(X['date_forecast'])
    X.drop(columns=['date_forecast'], inplace=True, errors='ignore')
    X.sort_values(by='ds', inplace=True)
    X.set_index('ds', inplace=True)


    X = feature_engineering(X)

    return X



def handle_features(X_train_observed, X_train_estimated, X_test, y_train):
    X_train_observed = fix_X(X_train_observed, "X_train_observed")
    X_train_estimated = fix_X(X_train_estimated, "X_train_estimated")
    X_test = fix_X(X_test, "X_test")


    if weight_evaluation:
        # add sample weights, which are 1 for observed and 3 for estimated
        X_train_observed["sample_weight"] = 1
        X_train_estimated["sample_weight"] = sample_weight_estimated
        X_test["sample_weight"] = sample_weight_estimated


    y_train['ds'] = pd.to_datetime(y_train['time'])
```

```python
    y_train.drop(columns=['time'], inplace=True)
    y_train.sort_values(by='ds', inplace=True)
    y_train.set_index('ds', inplace=True)

    return X_train_observed, X_train_estimated, X_test, y_train




def preprocess_data(X_train_observed, X_train_estimated, X_test, y_train,␣
 ↪location):
    # convert to datetime
    X_train_observed, X_train_estimated, X_test, y_train =␣
 ↪handle_features(X_train_observed, X_train_estimated, X_test, y_train)

    if use_estimated_diff_attr:
        X_train_observed["estimated_diff_hours"] = 0
        X_train_estimated["estimated_diff_hours"] = (X_train_estimated.index -␣
 ↪pd.to_datetime(X_train_estimated["date_calc"])).dt.total_seconds() / 3600
        X_test["estimated_diff_hours"] = (X_test.index - pd.
 ↪to_datetime(X_test["date_calc"])).dt.total_seconds() / 3600

        X_train_estimated["estimated_diff_hours"] =␣
 ↪X_train_estimated["estimated_diff_hours"].astype('int64')
        # the filled once will get dropped later anyways, when we drop y nans
        X_test["estimated_diff_hours"] = X_test["estimated_diff_hours"].
 ↪fillna(-50).astype('int64')

    if use_is_estimated_attr:
        X_train_observed["is_estimated"] = 0
        X_train_estimated["is_estimated"] = 1
        X_test["is_estimated"] = 1

    # drop date_calc
    X_train_estimated.drop(columns=['date_calc'], inplace=True)
    X_test.drop(columns=['date_calc'], inplace=True)


    y_train["y"] = y_train["pv_measurement"].astype('float64')
    y_train.drop(columns=['pv_measurement'], inplace=True)
    X_train = pd.concat([X_train_observed, X_train_estimated])


    # clip all y values to 0 if negative
    y_train["y"] = y_train["y"].clip(lower=0)
```

```python
    X_train = pd.merge(X_train, y_train, how="inner", left_index=True,␣
 ↪right_index=True)

    # print number of nans in y
    print(f"Number of nans in y: {X_train['y'].isna().sum()}")


    X_train["location"] = location
    X_test["location"] = location

    return X_train, X_test
# Define locations
locations = ['A', 'B', 'C']

X_trains = []
X_tests = []
# Loop through locations
for loc in locations:
    print(f"Processing location {loc}...")
    # Read target training data
    y_train = pd.read_parquet(f'{loc}/train_targets.parquet')

    # Read estimated training data and add location feature
    X_train_estimated = pd.read_parquet(f'{loc}/X_train_estimated.parquet')

    # Read observed training data and add location feature
    X_train_observed= pd.read_parquet(f'{loc}/X_train_observed.parquet')

    # Read estimated test data and add location feature
    X_test_estimated = pd.read_parquet(f'{loc}/X_test_estimated.parquet')

    # Preprocess data
    X_train, X_test = preprocess_data(X_train_observed, X_train_estimated,␣
 ↪X_test_estimated, y_train, loc)

    X_trains.append(X_train)
    X_tests.append(X_test)

# Concatenate all data and save to csv
X_train = pd.concat(X_trains)
X_test = pd.concat(X_tests)
```

```
Processing location A…
COUNT1 29667
COUNT2 1
index:  2019-06-02 22:00:00
index AFTER:  2019-06-02 22:00:00
```

```
COUNT1 4392
COUNT2 2
index:  2022-10-28 22:00:00
index AFTER:  2022-10-28 22:00:00
COUNT1 702
COUNT2 18
index:  2023-05-01 00:00:00
index AFTER:  2023-05-01 00:00:00
Number of nans in y: 0
Processing location B…
COUNT1 29232
COUNT2 1
index:  2019-01-01 00:00:00
index AFTER:  2019-01-01 00:00:00
COUNT1 4392
COUNT2 2
index:  2022-10-28 22:00:00
index AFTER:  2022-10-28 22:00:00
COUNT1 702
COUNT2 18
index:  2023-05-01 00:00:00
index AFTER:  2023-05-01 00:00:00
Number of nans in y: 4
Processing location C…
COUNT1 29206
COUNT2 1
index:  2019-01-01 00:00:00
index AFTER:  2019-01-01 00:00:00
COUNT1 4392
COUNT2 2
index:  2022-10-28 22:00:00
index AFTER:  2022-10-28 22:00:00
COUNT1 702
COUNT2 18
index:  2023-05-01 00:00:00
index AFTER:  2023-05-01 00:00:00
Number of nans in y: 6059
```

# 1 Feature enginering

[3]:
```
import numpy as np
import pandas as pd

X_train.dropna(subset=['y', 'direct_rad_1h:J', 'diffuse_rad_1h:J'],␣
 ↪inplace=True)
```

```python
for attr in use_dt_attrs:
    X_train[attr] = getattr(X_train.index, attr)
    X_test[attr] = getattr(X_test.index, attr)

print(X_train.head())
```

```python
if use_groups:
    # fix groups for cross validation
    locations = X_train['location'].unique()  # Assuming 'location' is the name␣
 ↪of the column representing locations

    grouped_dfs = []  # To store data frames split by location

    # Loop through each unique location
    for loc in locations:
        loc_df = X_train[X_train['location'] == loc]

        # Sort the DataFrame for this location by the time column
        loc_df = loc_df.sort_index()

        # Calculate the size of each group for this location
        group_size = len(loc_df) // n_groups

        # Create a new 'group' column for this location
        loc_df['group'] = np.repeat(range(n_groups),␣
 ↪repeats=[group_size]*(n_groups-1) + [len(loc_df) - group_size*(n_groups-1)])

        # Append to list of grouped DataFrames
        grouped_dfs.append(loc_df)

    # Concatenate all the grouped DataFrames back together
    X_train = pd.concat(grouped_dfs)
    X_train.sort_index(inplace=True)
    print(X_train["group"].head())
```

```python
to_drop = ["snow_drift:idx", "snow_density:kgm3", "wind_speed_w_1000hPa:ms",␣
 ↪"dew_or_rime:idx", "prob_rime:p", "fresh_snow_12h:cm", "fresh_snow_24h:cm",␣
 ↪"wind_speed_u_10m:ms", "wind_speed_v_10m:ms", "snow_melt_10min:mm",␣
 ↪"rain_water:kgm2", "dew_point_2m:K", "precip_5min:mm", "absolute_humidity_2m:
 ↪gm3", "air_density_2m:kgm3"]
```

```python
X_train.drop(columns=to_drop, inplace=True)
X_test.drop(columns=to_drop, inplace=True)

X_train.to_csv('X_train_raw.csv', index=True)
X_test.to_csv('X_test_raw.csv', index=True)
```

```
                     absolute_humidity_2m:gm3  air_density_2m:kgm3  \
ds
2019-06-02 22:00:00                     7.700              1.22825
2019-06-02 23:00:00                     7.700              1.22350
2019-06-03 00:00:00                     7.875              1.21975
2019-06-03 01:00:00                     8.425              1.21800
2019-06-03 02:00:00                     8.950              1.21800

                     ceiling_height_agl:m  clear_sky_energy_1h:J  \
ds
2019-06-02 22:00:00           1728.949951               0.000000
2019-06-02 23:00:00           1689.824951               0.000000
2019-06-03 00:00:00           1563.224976               0.000000
2019-06-03 01:00:00           1283.425049            6546.899902
2019-06-03 02:00:00           1003.500000          102225.898438

                     clear_sky_rad:W  cloud_base_agl:m  dew_or_rime:idx  \
ds
2019-06-02 22:00:00             0.00       1728.949951              0.0
2019-06-02 23:00:00             0.00       1689.824951              0.0
2019-06-03 00:00:00             0.00       1563.224976              0.0
2019-06-03 01:00:00             0.75       1283.425049              0.0
2019-06-03 02:00:00            23.10       1003.500000              0.0

                     dew_point_2m:K  diffuse_rad:W  diffuse_rad_1h:J  …  \
ds                                                                    …
2019-06-02 22:00:00      280.299988          0.000          0.000000  …
2019-06-02 23:00:00      280.299988          0.000          0.000000  …
2019-06-03 00:00:00      280.649994          0.000          0.000000  …
2019-06-03 01:00:00      281.674988          0.300       7743.299805  …
2019-06-03 02:00:00      282.500000         11.975      60137.601562  …

                     visibility:m  wind_speed_10m:ms  wind_speed_u_10m:ms  \
ds
2019-06-02 22:00:00  40386.476562              3.600               -3.575
2019-06-02 23:00:00  33770.648438              3.350               -3.350
2019-06-03 00:00:00  13595.500000              3.050               -2.950
2019-06-03 01:00:00   2321.850098              2.725               -2.600
2019-06-03 02:00:00  11634.799805              2.550               -2.350

                     wind_speed_v_10m:ms  wind_speed_w_1000hPa:ms  \
```

```
ds
2019-06-02 22:00:00              -0.500                     0.0
2019-06-02 23:00:00               0.275                     0.0
2019-06-03 00:00:00               0.750                     0.0
2019-06-03 01:00:00               0.875                     0.0
2019-06-03 02:00:00               0.925                     0.0

                     is_estimated      y  location  hour  year
ds
2019-06-02 22:00:00             0   0.00         A    22  2019
2019-06-02 23:00:00             0   0.00         A    23  2019
2019-06-03 00:00:00             0   0.00         A     0  2019
2019-06-03 01:00:00             0   0.00         A     1  2019
2019-06-03 02:00:00             0  19.36         A     2  2019

[5 rows x 50 columns]
```

[4]:

```python
def normalize_sample_weights_per_location(df):
    for loc in locations:
        loc_df = df[df["location"] == loc]
        loc_df["sample_weight"] = loc_df["sample_weight"] /␣
 ↪loc_df["sample_weight"].sum() * loc_df.shape[0]
        df[df["location"] == loc] = loc_df
    return df

import pandas as pd
import numpy as np

def split_and_shuffle_data(input_data, num_bins, frac1):
    """
    Splits the input_data into num_bins and shuffles them, then divides the␣
 ↪bins into two datasets based on the given fraction for the first set.

    Args:
        input_data (pd.DataFrame): The data to be split and shuffled.
        num_bins (int): The number of bins to split the data into.
        frac1 (float): The fraction of each bin to go into the first output␣
 ↪dataset.

    Returns:
        pd.DataFrame, pd.DataFrame: The two output datasets.
    """
    # Validate the input fraction
    if frac1 < 0 or frac1 > 1:
        raise ValueError("frac1 must be between 0 and 1.")

    if frac1==1:
```

```
        return input_data, pd.DataFrame()

    # Calculate the fraction for the second output set
    frac2 = 1 - frac1

    # Calculate bin size
    bin_size = len(input_data) // num_bins

    # Initialize empty DataFrames for output
    output_data1 = pd.DataFrame()
    output_data2 = pd.DataFrame()

    for i in range(num_bins):
        # Shuffle the data in the current bin
        np.random.seed(i)
        current_bin = input_data.iloc[i * bin_size: (i + 1) * bin_size].
↪sample(frac=1)

        # Calculate the sizes for each output set
        size1 = int(len(current_bin) * frac1)

        # Split and append to output DataFrames
        output_data1 = pd.concat([output_data1, current_bin.iloc[:size1]])
        output_data2 = pd.concat([output_data2, current_bin.iloc[size1:]])

    # Shuffle and split the remaining data
    remaining_data = input_data.iloc[num_bins * bin_size:].sample(frac=1)
    remaining_size1 = int(len(remaining_data) * frac1)

    output_data1 = pd.concat([output_data1, remaining_data.iloc[:
↪remaining_size1]])
    output_data2 = pd.concat([output_data2, remaining_data.iloc[remaining_size1:
↪]])

    return output_data1, output_data2
```

[5]:
```
from autogluon.tabular import TabularDataset, TabularPredictor
from autogluon.timeseries import TimeSeriesDataFrame
import numpy as np
data = TabularDataset('X_train_raw.csv')
# set group column of train_data be increasing from 0 to 7 based on time, the␣
↪first 1/8 of the data is group 0, the second 1/8 of the data is group 1, etc.
data['ds'] = pd.to_datetime(data['ds'])
data = data.sort_values(by='ds')

# # print size of the group for each location
# for loc in locations:
```

```
#     print(f"Location {loc}:")
#     print(train_data[train_data["location"] == loc].groupby('group').size())


# get end date of train data and subtract 3 months
#split_time = pd.to_datetime(train_data["ds"]).max() - pd.
↪Timedelta(hours=tune_and_test_length)
# 2022-10-28 22:00:00
split_time = pd.to_datetime("2022-10-28 22:00:00")
train_set = TabularDataset(data[data["ds"] < split_time])
test_set = TabularDataset(data[data["ds"] >= split_time])

# shuffle test_set and only grab tune_and_test_length percent of it, rest goes␣
↪to train_set
test_set, new_train_set = split_and_shuffle_data(test_set, 40,␣
↪tune_and_test_length)


print("Length of train set before adding test set", len(train_set))
# add rest to train_set
train_set = pd.concat([train_set, new_train_set])
print("Length of train set after adding test set", len(train_set))
print("Length of test set", len(test_set))




if use_groups:
    test_set = test_set.drop(columns=['group'])


tuning_data = None
if use_tune_data:
    if use_test_data:
        # split test_set in half, use first half for tuning
        tuning_data, test_data = [], []
        for loc in locations:
            loc_test_set = test_set[test_set["location"] == loc]
            # randomly shuffle the loc_test_set
            loc_tuning_data, loc_test_data =␣
↪split_and_shuffle_data(loc_test_set, 40, 0.5)
            tuning_data.append(loc_tuning_data)
            test_data.append(loc_test_data)
        tuning_data = pd.concat(tuning_data)
        test_data = pd.concat(test_data)
        print("Shapes of tuning and test", tuning_data.shape[0], test_data.
↪shape[0], tuning_data.shape[0] + test_data.shape[0])
```

```
    else:
        tuning_data = test_set
        print("Shape of tuning", tuning_data.shape[0])

    # ensure sample weights for your tuning data sum to the number of rows in␣
 ↪the tuning data.
    if weight_evaluation:
        tuning_data = normalize_sample_weights_per_location(tuning_data)


else:
    if use_test_data:
        test_data = test_set
        print("Shape of test", test_data.shape[0])


train_data = train_set

# ensure sample weights for your training (or tuning) data sum to the number of␣
 ↪rows in the training (or tuning) data.
if weight_evaluation:
    train_data = normalize_sample_weights_per_location(train_data)
    if use_test_data:
        test_data = normalize_sample_weights_per_location(test_data)


train_data = TabularDataset(train_data)
if use_tune_data:
    tuning_data = TabularDataset(tuning_data)
if use_test_data:
    test_data = TabularDataset(test_data)
```

```
Length of train set before adding test set 82026
Length of train set after adding test set 87486
Length of test set 5459
Shapes of tuning and test 2728 2731 5459
```

[6]:
```
if run_analysis:
    import autogluon.eda.auto as auto
    auto.dataset_overview(train_data=train_data, test_data=test_data,␣
 ↪label="y", sample=None)
```

**train_data dataset summary**

```
                                count  unique                  top   freq  \
ceiling_height_agl:m            72280   59980
clear_sky_energy_1h:J           87486   46359
clear_sky_rad:W                 87486   19918
```

| | | | | |
|---|---|---|---|---|
| cloud_base_agl:m | 81454 | 61360 | | |
| diffuse_rad:W | 87486 | 11092 | | |
| diffuse_rad_1h:J | 87486 | 46319 | | |
| direct_rad:W | 87486 | 14181 | | |
| direct_rad_1h:J | 87486 | 40118 | | |
| ds | 87486 | 36794 | 2021-02-05 14:00:00 | 3 |
| effective_cloud_cover:p | 87486 | 5655 | | |
| elevation:m | 87486 | 3 | | |
| fresh_snow_1h:cm | 87486 | 39 | | |
| fresh_snow_3h:cm | 87486 | 70 | | |
| fresh_snow_6h:cm | 87486 | 96 | | |
| hour | 87486 | 24 | | |
| is_day:idx | 87486 | 5 | | |
| is_estimated | 87486 | 2 | | |
| is_in_shadow:idx | 87486 | 5 | | |
| location | 87486 | 3 | A | 31872 |
| msl_pressure:hPa | 87486 | 3708 | | |
| precip_type_5min:idx | 87486 | 15 | | |
| pressure_100m:hPa | 87486 | 3730 | | |
| pressure_50m:hPa | 87486 | 3775 | | |
| relative_humidity_1000hPa:p | 87486 | 3799 | | |
| sfc_pressure:hPa | 87486 | 3795 | | |
| snow_depth:cm | 87486 | 487 | | |
| snow_water:kgm2 | 87486 | 161 | | |
| sun_azimuth:d | 87486 | 83179 | | |
| sun_elevation:d | 87486 | 72262 | | |
| super_cooled_liquid_water:kgm2 | 87486 | 53 | | |
| t_1000hPa:K | 87486 | 1989 | | |
| total_cloud_cover:p | 87486 | 5556 | | |
| visibility:m | 87486 | 85949 | | |
| wind_speed_10m:ms | 87486 | 596 | | |
| y | 87486 | 11321 | | |
| year | 87486 | 5 | | |

| | first | last | mean | \ |
|---|---|---|---|---|
| ceiling_height_agl:m | NaT | NaT | 2861.929806 | |
| clear_sky_energy_1h:J | NaT | NaT | 530297.395771 | |
| clear_sky_rad:W | NaT | NaT | 147.308425 | |
| cloud_base_agl:m | NaT | NaT | 1740.241802 | |
| diffuse_rad:W | NaT | NaT | 40.267497 | |
| diffuse_rad_1h:J | NaT | NaT | 145328.6257 | |
| direct_rad:W | NaT | NaT | 51.524847 | |
| direct_rad_1h:J | NaT | NaT | 185338.05854 | |
| ds | 2019-01-01 | 2023-04-30 22:00:00 | | |
| effective_cloud_cover:p | NaT | NaT | 67.052836 | |
| elevation:m | NaT | NaT | 11.414718 | |
| fresh_snow_1h:cm | NaT | NaT | 0.008783 | |
| fresh_snow_3h:cm | NaT | NaT | 0.026713 | |

| | | | |
|---|---|---|---|
| fresh_snow_6h:cm | NaT | NaT | 0.05322 |
| hour | NaT | NaT | 11.499589 |
| is_day:idx | NaT | NaT | 0.490147 |
| is_estimated | NaT | NaT | 0.06241 |
| is_in_shadow:idx | NaT | NaT | 0.556952 |
| location | NaT | NaT | |
| msl_pressure:hPa | NaT | NaT | 1009.434307 |
| precip_type_5min:idx | NaT | NaT | 0.084976 |
| pressure_100m:hPa | NaT | NaT | 995.759729 |
| pressure_50m:hPa | NaT | NaT | 1001.884211 |
| relative_humidity_1000hPa:p | NaT | NaT | 73.779918 |
| sfc_pressure:hPa | NaT | NaT | 1008.035963 |
| snow_depth:cm | NaT | NaT | 0.197574 |
| snow_water:kgm2 | NaT | NaT | 0.090839 |
| sun_azimuth:d | NaT | NaT | 179.584247 |
| sun_elevation:d | NaT | NaT | -0.705998 |
| super_cooled_liquid_water:kgm2 | NaT | NaT | 0.058256 |
| t_1000hPa:K | NaT | NaT | 279.675551 |
| total_cloud_cover:p | NaT | NaT | 73.72398 |
| visibility:m | NaT | NaT | 32944.238197 |
| wind_speed_10m:ms | NaT | NaT | 3.032943 |
| y | NaT | NaT | 294.447861 |
| year | NaT | NaT | 2020.568365 |

| | std | min | 25% | 50% | \ |
|---|---|---|---|---|---|
| ceiling_height_agl:m | 2532.377528 | 27.8 | 1082.3125 | 1856.075 | |
| clear_sky_energy_1h:J | 831839.646633 | 0.0 | 0.0 | 9084.9 | |
| clear_sky_rad:W | 231.107565 | 0.0 | 0.0 | 2.325 | |
| cloud_base_agl:m | 1808.519208 | 27.5 | 598.15625 | 1174.775 | |
| diffuse_rad:W | 61.119566 | 0.0 | 0.0 | 1.35 | |
| diffuse_rad_1h:J | 218036.296903 | 0.0 | 0.0 | 12531.2 | |
| direct_rad:W | 114.236728 | 0.0 | 0.0 | 0.0 | |
| direct_rad_1h:J | 406379.39471 | 0.0 | 0.0 | 0.0 | |
| ds | | | | | |
| effective_cloud_cover:p | 34.132847 | 0.0 | 42.125 | 79.7 | |
| elevation:m | 7.881545 | 6.0 | 6.0 | 7.0 | |
| fresh_snow_1h:cm | 0.110515 | 0.0 | 0.0 | 0.0 | |
| fresh_snow_3h:cm | 0.277575 | 0.0 | 0.0 | 0.0 | |
| fresh_snow_6h:cm | 0.474579 | 0.0 | 0.0 | 0.0 | |
| hour | 6.920464 | 0.0 | 5.0 | 12.0 | |
| is_day:idx | 0.486133 | 0.0 | 0.0 | 0.5 | |
| is_estimated | 0.2419 | 0.0 | 0.0 | 0.0 | |
| is_in_shadow:idx | 0.484138 | 0.0 | 0.0 | 1.0 | |
| location | | | | | |
| msl_pressure:hPa | 12.993994 | 944.375 | 1001.45 | 1010.325 | |
| precip_type_5min:idx | 0.32995 | 0.0 | 0.0 | 0.0 | |
| pressure_100m:hPa | 12.922092 | 929.975 | 987.85 | 996.75 | |
| pressure_50m:hPa | 12.979336 | 935.75 | 993.925012 | 1002.85 | |

```
relative_humidity_1000hPa:p        14.200631    19.575        64.4       76.15
sfc_pressure:hPa                   13.038723    941.55     1000.05      1009.0
snow_depth:cm                        1.28439       0.0         0.0         0.0
snow_water:kgm2                     0.240248       0.0         0.0         0.0
sun_azimuth:d                      97.419022     6.983     94.4135   180.00663
sun_elevation:d                    24.006117   -49.932  -17.969875   -0.453875
super_cooled_liquid_water:kgm2      0.106959       0.0         0.0         0.0
t_1000hPa:K                         6.551665   258.025       275.1     278.975
total_cloud_cover:p                33.851299       0.0      53.475      92.825
visibility:m                     17949.64428   132.375  16564.5125    36910.75
wind_speed_10m:ms                   1.758713     0.025       1.675         2.7
y                                 774.531815      -0.0         0.0         0.0
year                                1.102625    2019.0      2020.0      2021.0

                                        75%        max           dtypes  \
ceiling_height_agl:m             3916.78125  12285.775          float64
clear_sky_energy_1h:J            831169.675  3006697.2          float64
clear_sky_rad:W                   231.34375     835.65          float64
cloud_base_agl:m                 2080.39375  11673.725          float64
diffuse_rad:W                         67.15     334.75          float64
diffuse_rad_1h:J                 243365.275  1182265.4          float64
direct_rad:W                         32.225      683.4          float64
direct_rad_1h:J                  122454.125  2445897.0          float64
ds                                                       datetime64[ns]
effective_cloud_cover:p                98.5      100.0          float64
elevation:m                            24.0       24.0          float64
fresh_snow_1h:cm                        0.0        7.1          float64
fresh_snow_3h:cm                        0.0       20.6          float64
fresh_snow_6h:cm                        0.0       34.0          float64
hour                                   17.0       23.0            int64
is_day:idx                              1.0        1.0          float64
is_estimated                            0.0        1.0            int64
is_in_shadow:idx                        1.0        1.0          float64
location                                                         object
msl_pressure:hPa                 1018.42505     1044.1          float64
precip_type_5min:idx                    0.0        5.0          float64
pressure_100m:hPa                    1004.8   1030.875          float64
pressure_50m:hPa                 1010.92505    1037.25          float64
relative_humidity_1000hPa:p          85.175      100.0          float64
sfc_pressure:hPa                     1017.1   1043.725          float64
snow_depth:cm                           0.0       18.2          float64
snow_water:kgm2                         0.1       5.65          float64
sun_azimuth:d                    264.601138  348.48752          float64
sun_elevation:d                   16.004499   49.94375          float64
super_cooled_liquid_water:kgm2          0.1      1.375          float64
t_1000hPa:K                         284.225     303.25          float64
total_cloud_cover:p                    99.9      100.0          float64
visibility:m                       48289.05   75326.58          float64
```

| | | | |
|---|---|---|---|
| wind_speed_10m:ms | 4.05 | 13.275 | float64 |
| y | 183.7125 | 5733.42 | float64 |
| year | 2021.0 | 2023.0 | int64 |

| | missing_count | missing_ratio | raw_type \ |
|---|---|---|---|
| ceiling_height_agl:m | 15206 | 0.173811 | float |
| clear_sky_energy_1h:J | | | float |
| clear_sky_rad:W | | | float |
| cloud_base_agl:m | 6032 | 0.068948 | float |
| diffuse_rad:W | | | float |
| diffuse_rad_1h:J | | | float |
| direct_rad:W | | | float |
| direct_rad_1h:J | | | float |
| ds | | | datetime |
| effective_cloud_cover:p | | | float |
| elevation:m | | | float |
| fresh_snow_1h:cm | | | float |
| fresh_snow_3h:cm | | | float |
| fresh_snow_6h:cm | | | float |
| hour | | | int |
| is_day:idx | | | float |
| is_estimated | | | int |
| is_in_shadow:idx | | | float |
| location | | | object |
| msl_pressure:hPa | | | float |
| precip_type_5min:idx | | | float |
| pressure_100m:hPa | | | float |
| pressure_50m:hPa | | | float |
| relative_humidity_1000hPa:p | | | float |
| sfc_pressure:hPa | | | float |
| snow_depth:cm | | | float |
| snow_water:kgm2 | | | float |
| sun_azimuth:d | | | float |
| sun_elevation:d | | | float |
| super_cooled_liquid_water:kgm2 | | | float |
| t_1000hPa:K | | | float |
| total_cloud_cover:p | | | float |
| visibility:m | | | float |
| wind_speed_10m:ms | | | float |
| y | | | float |
| year | | | int |

| | variable_type | special_types |
|---|---|---|
| ceiling_height_agl:m | numeric | |
| clear_sky_energy_1h:J | numeric | |
| clear_sky_rad:W | numeric | |
| cloud_base_agl:m | numeric | |
| diffuse_rad:W | numeric | |

| | |
|---|---|
| diffuse_rad_1h:J | numeric |
| direct_rad:W | numeric |
| direct_rad_1h:J | numeric |
| ds | |
| effective_cloud_cover:p | numeric |
| elevation:m | category |
| fresh_snow_1h:cm | numeric |
| fresh_snow_3h:cm | numeric |
| fresh_snow_6h:cm | numeric |
| hour | numeric |
| is_day:idx | category |
| is_estimated | category |
| is_in_shadow:idx | category |
| location | category |
| msl_pressure:hPa | numeric |
| precip_type_5min:idx | category |
| pressure_100m:hPa | numeric |
| pressure_50m:hPa | numeric |
| relative_humidity_1000hPa:p | numeric |
| sfc_pressure:hPa | numeric |
| snow_depth:cm | numeric |
| snow_water:kgm2 | numeric |
| sun_azimuth:d | numeric |
| sun_elevation:d | numeric |
| super_cooled_liquid_water:kgm2 | numeric |
| t_1000hPa:K | numeric |
| total_cloud_cover:p | numeric |
| visibility:m | numeric |
| wind_speed_10m:ms | numeric |
| y | numeric |
| year | category |

**test_data dataset summary**

| | count | unique | top | freq | \ |
|---|---|---|---|---|---|
| ceiling_height_agl:m | 2100 | 2065 | | | |
| clear_sky_energy_1h:J | 2731 | 1138 | | | |
| clear_sky_rad:W | 2731 | 997 | | | |
| cloud_base_agl:m | 2374 | 2332 | | | |
| diffuse_rad:W | 2731 | 983 | | | |
| diffuse_rad_1h:J | 2731 | 1138 | | | |
| direct_rad:W | 2731 | 750 | | | |
| direct_rad_1h:J | 2731 | 932 | | | |
| ds | 2731 | 2200 | 2023-04-10 19:00:00 | 3 | |
| effective_cloud_cover:p | 2731 | 1348 | | | |
| elevation:m | 2731 | 3 | | | |
| fresh_snow_1h:cm | 2731 | 19 | | | |
| fresh_snow_3h:cm | 2731 | 36 | | | |
| fresh_snow_6h:cm | 2731 | 50 | | | |

| | | | | |
|---|---|---|---|---|
| hour | 2731 | 24 | | |
| is_day:idx | 2731 | 5 | | |
| is_estimated | 2731 | 1 | | |
| is_in_shadow:idx | 2731 | 5 | | |
| location | 2731 | 3 | A | 1094 |
| msl_pressure:hPa | 2731 | 1525 | | |
| precip_type_5min:idx | 2731 | 10 | | |
| pressure_100m:hPa | 2731 | 1536 | | |
| pressure_50m:hPa | 2731 | 1557 | | |
| relative_humidity_1000hPa:p | 2731 | 1523 | | |
| sfc_pressure:hPa | 2731 | 1575 | | |
| snow_depth:cm | 2731 | 61 | | |
| snow_water:kgm2 | 2731 | 61 | | |
| sun_azimuth:d | 2731 | 2716 | | |
| sun_elevation:d | 2731 | 2652 | | |
| super_cooled_liquid_water:kgm2 | 2731 | 29 | | |
| t_1000hPa:K | 2731 | 774 | | |
| total_cloud_cover:p | 2731 | 1126 | | |
| visibility:m | 2731 | 2729 | | |
| wind_speed_10m:ms | 2731 | 366 | | |
| y | 2731 | 895 | | |
| year | 2731 | 2 | | |

| | first | last \ |
|---|---|---|
| ceiling_height_agl:m | NaT | NaT |
| clear_sky_energy_1h:J | NaT | NaT |
| clear_sky_rad:W | NaT | NaT |
| cloud_base_agl:m | NaT | NaT |
| diffuse_rad:W | NaT | NaT |
| diffuse_rad_1h:J | NaT | NaT |
| direct_rad:W | NaT | NaT |
| direct_rad_1h:J | NaT | NaT |
| ds | 2022-10-28 22:00:00 | 2023-04-30 19:00:00 |
| effective_cloud_cover:p | NaT | NaT |
| elevation:m | NaT | NaT |
| fresh_snow_1h:cm | NaT | NaT |
| fresh_snow_3h:cm | NaT | NaT |
| fresh_snow_6h:cm | NaT | NaT |
| hour | NaT | NaT |
| is_day:idx | NaT | NaT |
| is_estimated | NaT | NaT |
| is_in_shadow:idx | NaT | NaT |
| location | NaT | NaT |
| msl_pressure:hPa | NaT | NaT |
| precip_type_5min:idx | NaT | NaT |
| pressure_100m:hPa | NaT | NaT |
| pressure_50m:hPa | NaT | NaT |
| relative_humidity_1000hPa:p | NaT | NaT |

| | | |
|---|---|---|
| sfc_pressure:hPa | NaT | NaT |
| snow_depth:cm | NaT | NaT |
| snow_water:kgm2 | NaT | NaT |
| sun_azimuth:d | NaT | NaT |
| sun_elevation:d | NaT | NaT |
| super_cooled_liquid_water:kgm2 | NaT | NaT |
| t_1000hPa:K | NaT | NaT |
| total_cloud_cover:p | NaT | NaT |
| visibility:m | NaT | NaT |
| wind_speed_10m:ms | NaT | NaT |
| y | NaT | NaT |
| year | NaT | NaT |

| | mean | std | min \ |
|---|---|---|---|
| ceiling_height_agl:m | 3361.682133 | 2562.862274 | 28.0 |
| clear_sky_energy_1h:J | 285528.142658 | 573252.521662 | 0.0 |
| clear_sky_rad:W | 79.243464 | 159.124874 | 0.0 |
| cloud_base_agl:m | 1685.111501 | 1833.56975 | 27.5 |
| diffuse_rad:W | 26.230813 | 48.360421 | 0.0 |
| diffuse_rad_1h:J | 94649.301538 | 172723.786046 | 0.0 |
| direct_rad:W | 32.798068 | 92.244541 | 0.0 |
| direct_rad_1h:J | 118054.008202 | 329601.815692 | 0.0 |
| ds | | | |
| effective_cloud_cover:p | 66.798654 | 36.717964 | 0.0 |
| elevation:m | 11.193336 | 7.806119 | 6.0 |
| fresh_snow_1h:cm | 0.023984 | 0.147555 | 0.0 |
| fresh_snow_3h:cm | 0.069498 | 0.352141 | 0.0 |
| fresh_snow_6h:cm | 0.13885 | 0.57722 | 0.0 |
| hour | 11.544855 | 6.879849 | 0.0 |
| is_day:idx | 0.378341 | 0.472171 | 0.0 |
| is_estimated | 1.0 | 0.0 | 1.0 |
| is_in_shadow:idx | 0.677133 | 0.452911 | 0.0 |
| location | | | |
| msl_pressure:hPa | 1010.736333 | 14.355902 | 972.15 |
| precip_type_5min:idx | 0.076254 | 0.344931 | 0.0 |
| pressure_100m:hPa | 996.906224 | 14.168772 | 959.19995 |
| pressure_50m:hPa | 1003.137999 | 14.243079 | 965.15 |
| relative_humidity_1000hPa:p | 71.631472 | 14.652551 | 21.7 |
| sfc_pressure:hPa | 1009.397775 | 14.318453 | 971.15 |
| snow_depth:cm | 0.119965 | 0.56196 | 0.0 |
| snow_water:kgm2 | 0.080511 | 0.19473 | 0.0 |
| sun_azimuth:d | 180.975998 | 94.222121 | 14.914 |
| sun_elevation:d | -8.945472 | 22.095926 | -49.887 |
| super_cooled_liquid_water:kgm2 | 0.035088 | 0.082444 | 0.0 |
| t_1000hPa:K | 275.52987 | 4.271781 | 259.975 |
| total_cloud_cover:p | 72.32056 | 37.085445 | 0.0 |
| visibility:m | 34504.948017 | 17242.154257 | 270.3 |
| wind_speed_10m:ms | 3.109676 | 1.782531 | 0.125 |

| | | | |
|---|---|---|---|
| y | 179.379421 | 641.546947 | 0.0 |
| year | 2022.693153 | 0.46127 | 2022.0 |

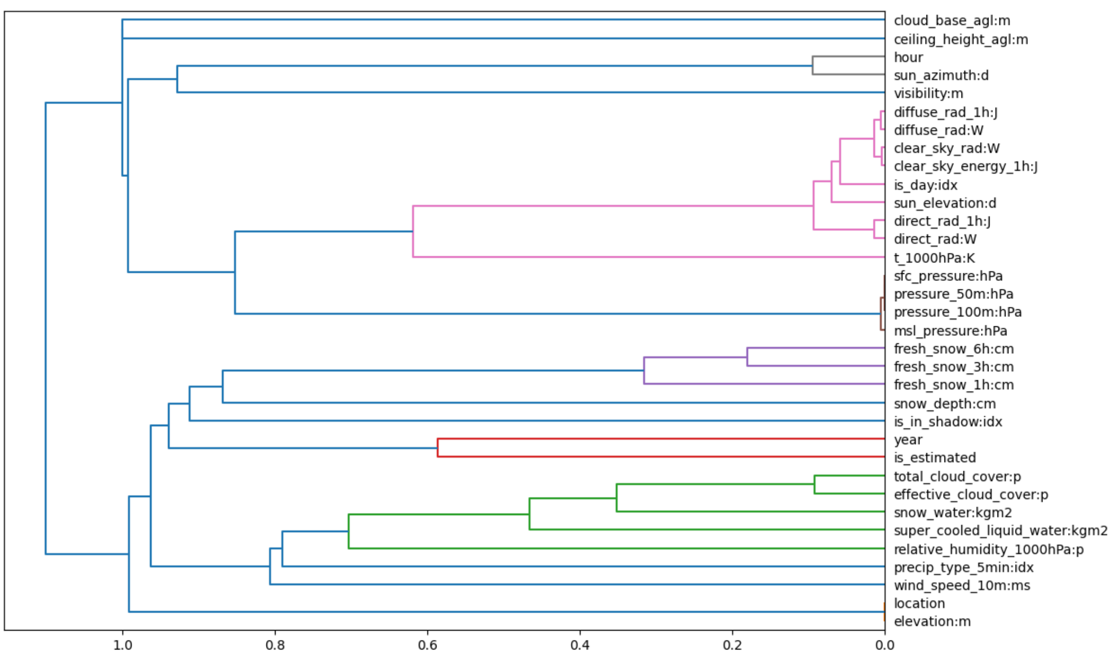
| | 25% | 50% | 75% | max \ |
|---|---|---|---|---|
| ceiling_height_agl:m | 1245.55625 | 2784.275 | 4919.18125 | 12294.9 |
| clear_sky_energy_1h:J | 0.0 | 0.0 | 220909.2 | 2551917.2 |
| clear_sky_rad:W | 0.0 | 0.0 | 62.7625 | 709.825 |
| cloud_base_agl:m | 516.7625 | 1000.8 | 2066.9875 | 10813.7 |
| diffuse_rad:W | 0.0 | 0.0 | 32.0 | 280.5 |
| diffuse_rad_1h:J | 0.0 | 0.0 | 116208.0 | 986147.0 |
| direct_rad:W | 0.0 | 0.0 | 4.7625 | 511.7 |
| direct_rad_1h:J | 0.0 | 0.0 | 24326.65 | 1844204.9 |
| ds | | | | |
| effective_cloud_cover:p | 36.3125 | 83.05 | 99.825 | 100.0 |
| elevation:m | 6.0 | 7.0 | 24.0 | 24.0 |
| fresh_snow_1h:cm | 0.0 | 0.0 | 0.0 | 2.3 |
| fresh_snow_3h:cm | 0.0 | 0.0 | 0.0 | 4.8 |
| fresh_snow_6h:cm | 0.0 | 0.0 | 0.0 | 6.3 |
| hour | 6.0 | 12.0 | 17.5 | 23.0 |
| is_day:idx | 0.0 | 0.0 | 1.0 | 1.0 |
| is_estimated | 1.0 | 1.0 | 1.0 | 1.0 |
| is_in_shadow:idx | 0.0 | 1.0 | 1.0 | 1.0 |
| location | | | | |
| msl_pressure:hPa | 1000.35 | 1010.6 | 1021.4625 | 1041.2 |
| precip_type_5min:idx | 0.0 | 0.0 | 0.0 | 3.0 |
| pressure_100m:hPa | 986.8 | 996.95 | 1007.675 | 1027.8 |
| pressure_50m:hPa | 992.9 | 1003.175 | 1014.0 | 1034.1 |
| relative_humidity_1000hPa:p | 61.775 | 73.55 | 82.9625 | 99.775 |
| sfc_pressure:hPa | 999.1 | 1009.5 | 1020.275 | 1040.6 |
| snow_depth:cm | 0.0 | 0.0 | 0.0 | 4.9 |
| snow_water:kgm2 | 0.0 | 0.0 | 0.1 | 2.15 |
| sun_azimuth:d | 101.047372 | 179.89075 | 260.65412 | 347.81226 |
| sun_elevation:d | -26.72725 | -8.178 | 6.393625 | 41.09175 |
| super_cooled_liquid_water:kgm2 | 0.0 | 0.0 | 0.0 | 0.75 |
| t_1000hPa:K | 272.6625 | 275.45 | 278.5 | 285.825 |
| total_cloud_cover:p | 44.5875 | 96.775 | 100.0 | 100.0 |
| visibility:m | 20902.55 | 36141.85 | 48867.949 | 73937.67 |
| wind_speed_10m:ms | 1.6 | 2.8 | 4.2375 | 9.9 |
| y | 0.0 | 0.0 | 40.397706 | 5043.72 |
| year | 2022.0 | 2023.0 | 2023.0 | 2023.0 |

| | dtypes | missing_count | missing_ratio \ |
|---|---|---|---|
| ceiling_height_agl:m | float64 | 631 | 0.231051 |
| clear_sky_energy_1h:J | float64 | | |
| clear_sky_rad:W | float64 | | |
| cloud_base_agl:m | float64 | 357 | 0.130721 |
| diffuse_rad:W | float64 | | |
| diffuse_rad_1h:J | float64 | | |

```
direct_rad:W                              float64
direct_rad_1h:J                           float64
ds                                 datetime64[ns]
effective_cloud_cover:p                   float64
elevation:m                               float64
fresh_snow_1h:cm                          float64
fresh_snow_3h:cm                          float64
fresh_snow_6h:cm                          float64
hour                                        int64
is_day:idx                                float64
is_estimated                                int64
is_in_shadow:idx                          float64
location                                   object
msl_pressure:hPa                          float64
precip_type_5min:idx                      float64
pressure_100m:hPa                         float64
pressure_50m:hPa                          float64
relative_humidity_1000hPa:p               float64
sfc_pressure:hPa                          float64
snow_depth:cm                             float64
snow_water:kgm2                           float64
sun_azimuth:d                             float64
sun_elevation:d                           float64
super_cooled_liquid_water:kgm2            float64
t_1000hPa:K                               float64
total_cloud_cover:p                       float64
visibility:m                              float64
wind_speed_10m:ms                         float64
y                                         float64
year                                        int64

                               raw_type variable_type special_types
ceiling_height_agl:m              float       numeric
clear_sky_energy_1h:J             float       numeric
clear_sky_rad:W                   float       numeric
cloud_base_agl:m                  float       numeric
diffuse_rad:W                     float       numeric
diffuse_rad_1h:J                  float       numeric
direct_rad:W                      float       numeric
direct_rad_1h:J                   float       numeric
ds                             datetime
effective_cloud_cover:p           float       numeric
elevation:m                       float      category
fresh_snow_1h:cm                  float      category
fresh_snow_3h:cm                  float       numeric
fresh_snow_6h:cm                  float       numeric
hour                                int       numeric
is_day:idx                        float      category
```

| | | |
|---|---|---|
| is_estimated | int | category |
| is_in_shadow:idx | float | category |
| location | object | category |
| msl_pressure:hPa | float | numeric |
| precip_type_5min:idx | float | category |
| pressure_100m:hPa | float | numeric |
| pressure_50m:hPa | float | numeric |
| relative_humidity_1000hPa:p | float | numeric |
| sfc_pressure:hPa | float | numeric |
| snow_depth:cm | float | numeric |
| snow_water:kgm2 | float | numeric |
| sun_azimuth:d | float | numeric |
| sun_elevation:d | float | numeric |
| super_cooled_liquid_water:kgm2 | float | numeric |
| t_1000hPa:K | float | numeric |
| total_cloud_cover:p | float | numeric |
| visibility:m | float | numeric |
| wind_speed_10m:ms | float | numeric |
| y | float | numeric |
| year | int | category |

### 1.0.1 Feature Distance



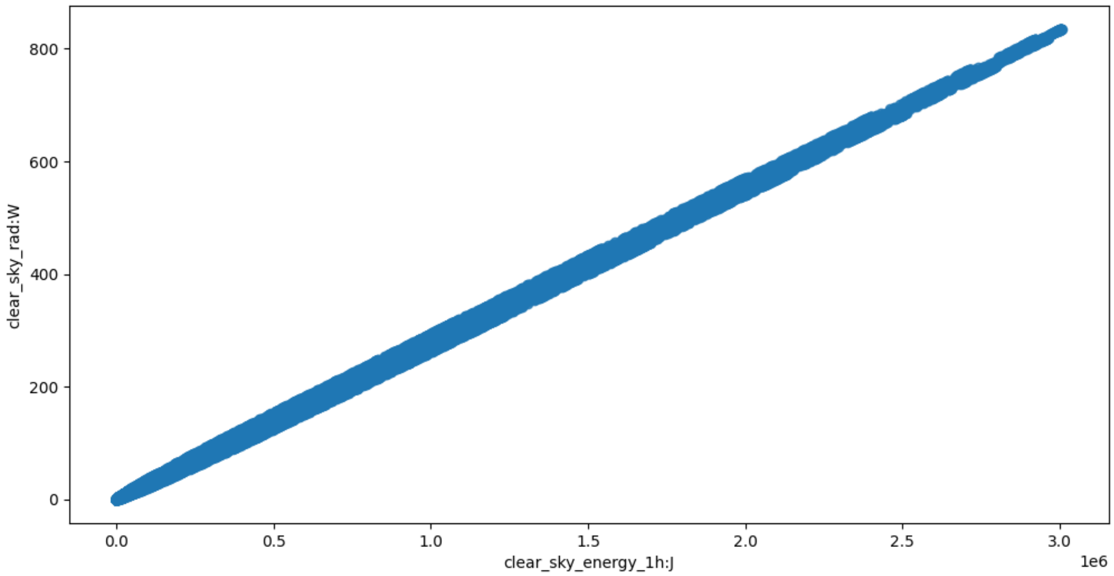

**The following feature groups are considered as near-duplicates**:

Distance threshold: <= `0.01`. Consider keeping only some of the columns within each group:

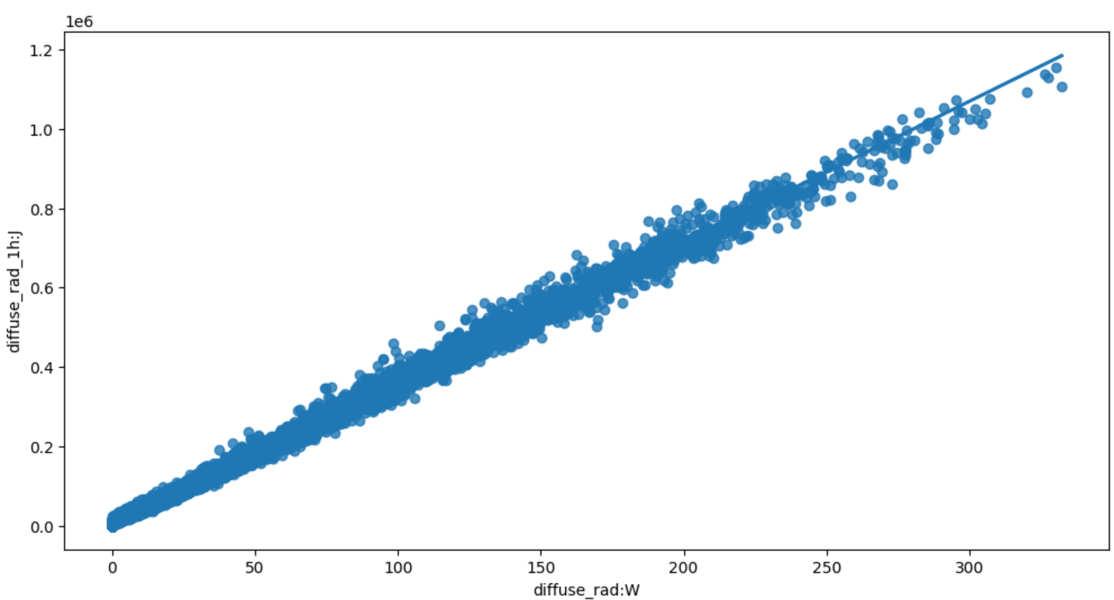
- `elevation:m`, `location` - distance `0.00`

- `clear_sky_energy_1h:J`, `clear_sky_rad:W` - distance `0.00`
- `diffuse_rad:W`, `diffuse_rad_1h:J` - distance `0.00`
- `msl_pressure:hPa`, `pressure_100m:hPa`, `pressure_50m:hPa`, `sfc_pressure:hPa` - distance `0.00`

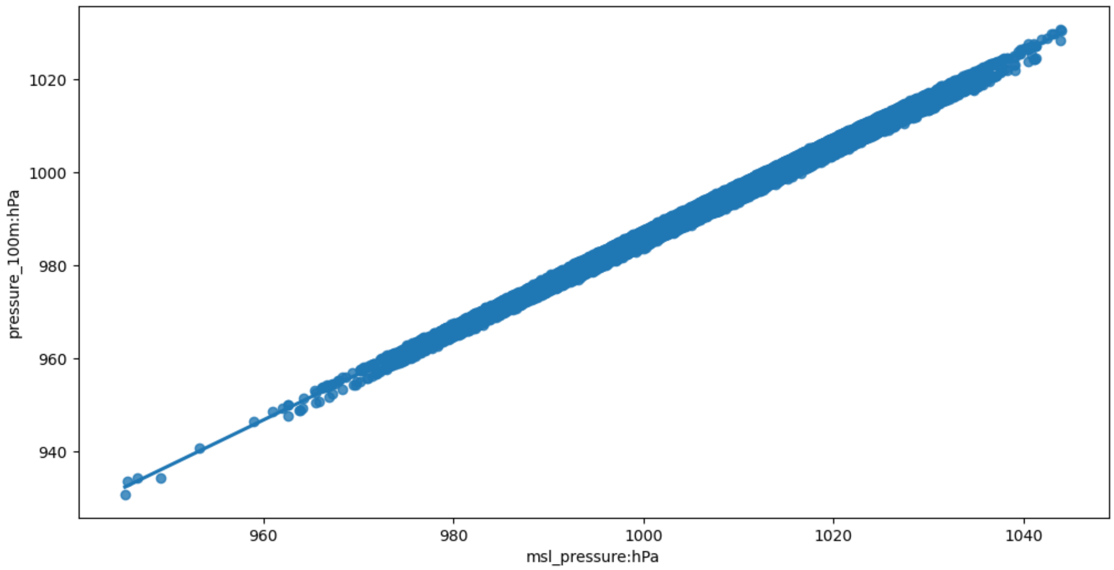
Feature interaction between `clear_sky_energy_1h:J/clear_sky_rad:W`



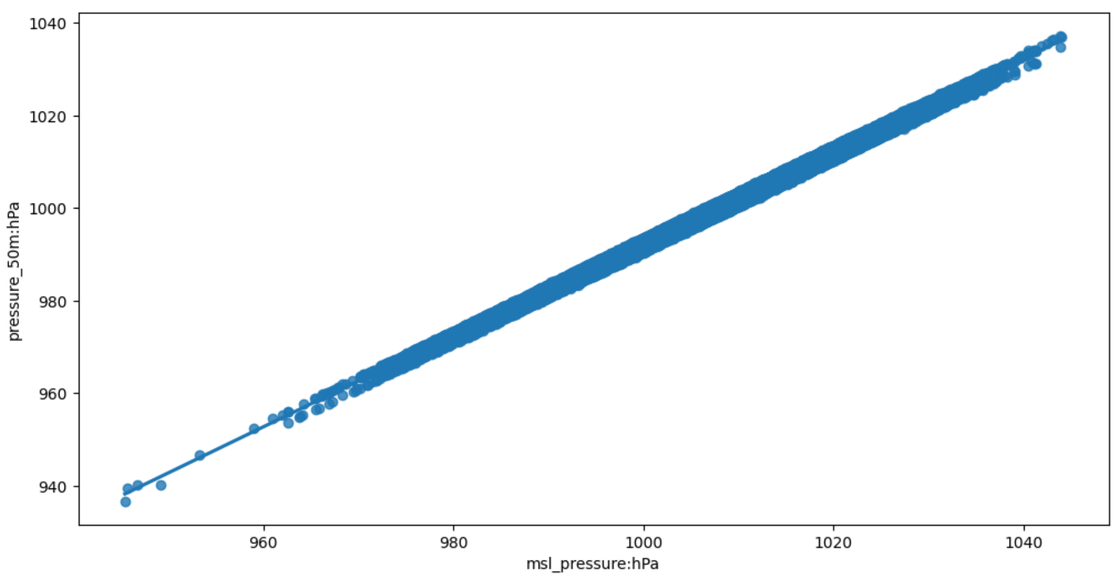

Feature interaction between `diffuse_rad:W/diffuse_rad_1h:J`



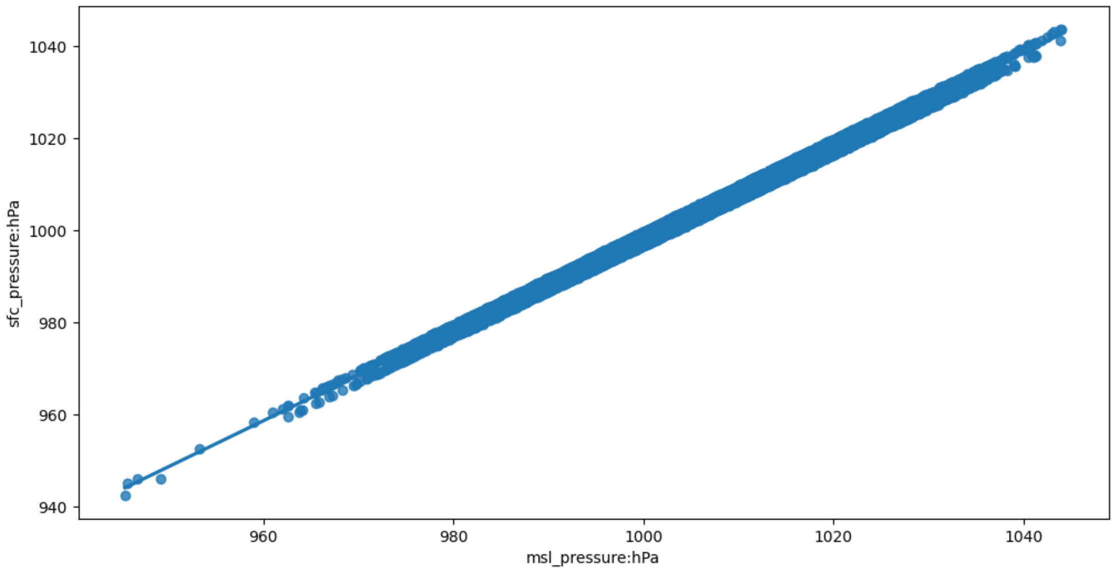
Feature interaction between `msl_pressure:hPa/pressure_100m:hPa`




Feature interaction between `msl_pressure:hPa/pressure_50m:hPa`




Feature interaction between `msl_pressure:hPa/sfc_pressure:hPa`

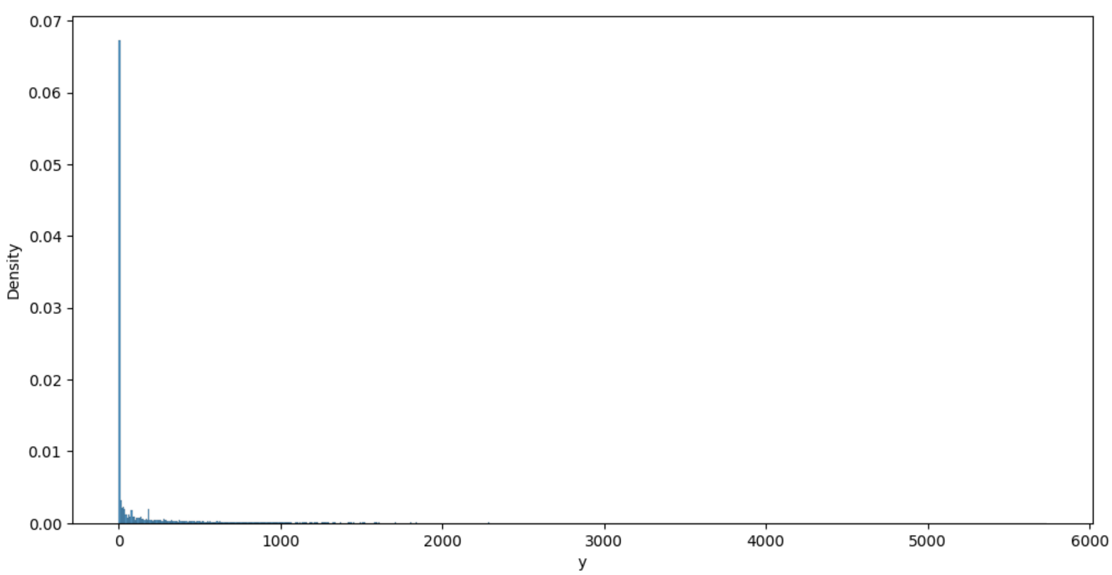



[7]:

```
if run_analysis:
    auto.target_analysis(train_data=train_data, label="y", sample=None)
```

## 1.1 Target variable analysis

```
   count        mean         std   min  25%  50%       75%      max   dtypes  \
y  87486  294.447861  774.531815  -0.0  0.0  0.0  183.7125  5733.42  float64

   unique missing_count missing_ratio raw_type special_types
y   11321                                 float
```

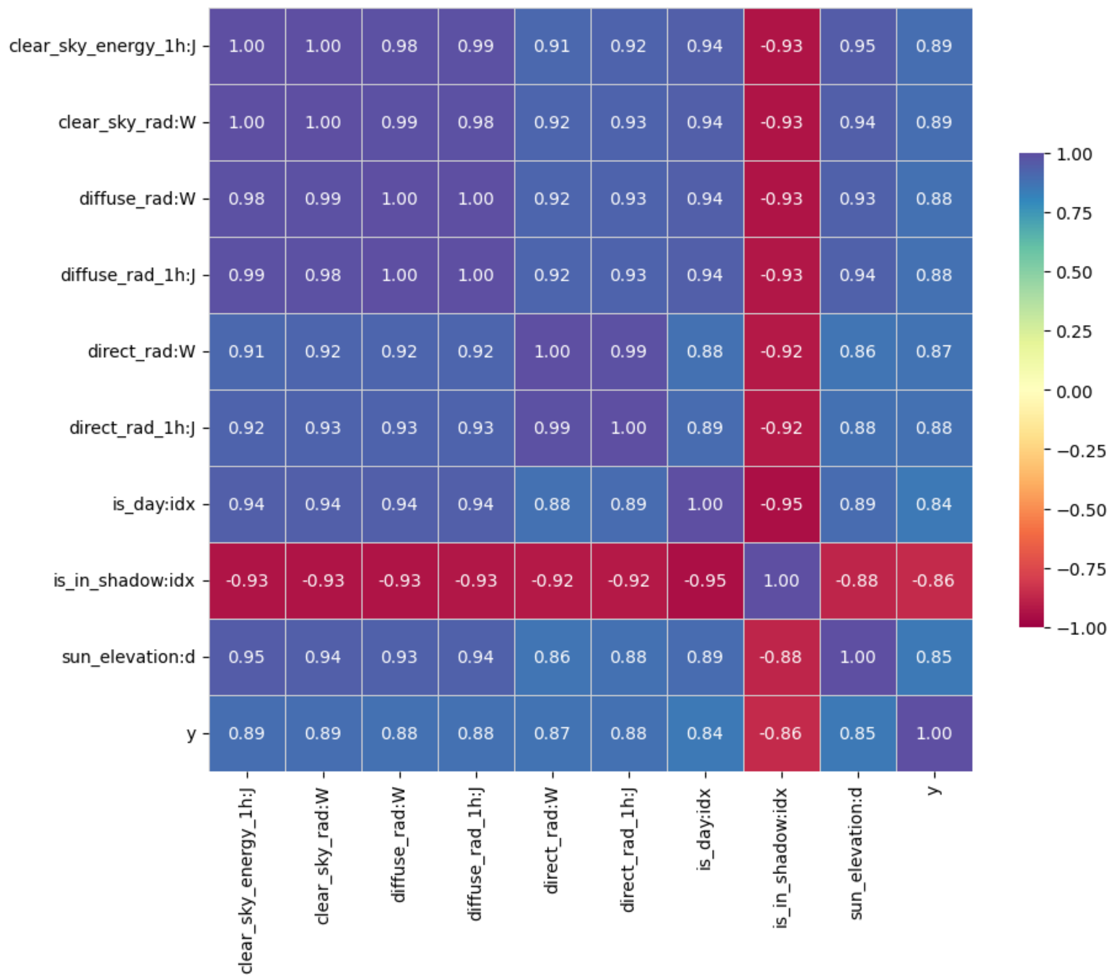


### 1.1.1 Distribution fits for target variable

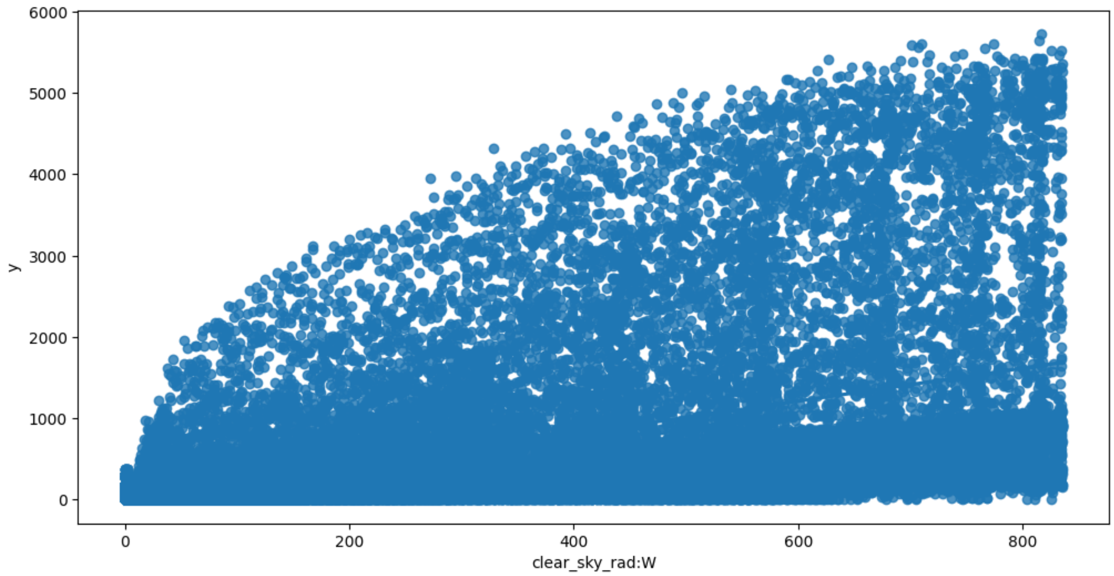
- none of the attempted distribution fits satisfy specified minimum p-value threshold: `0.01`

### 1.1.2 Target variable correlations

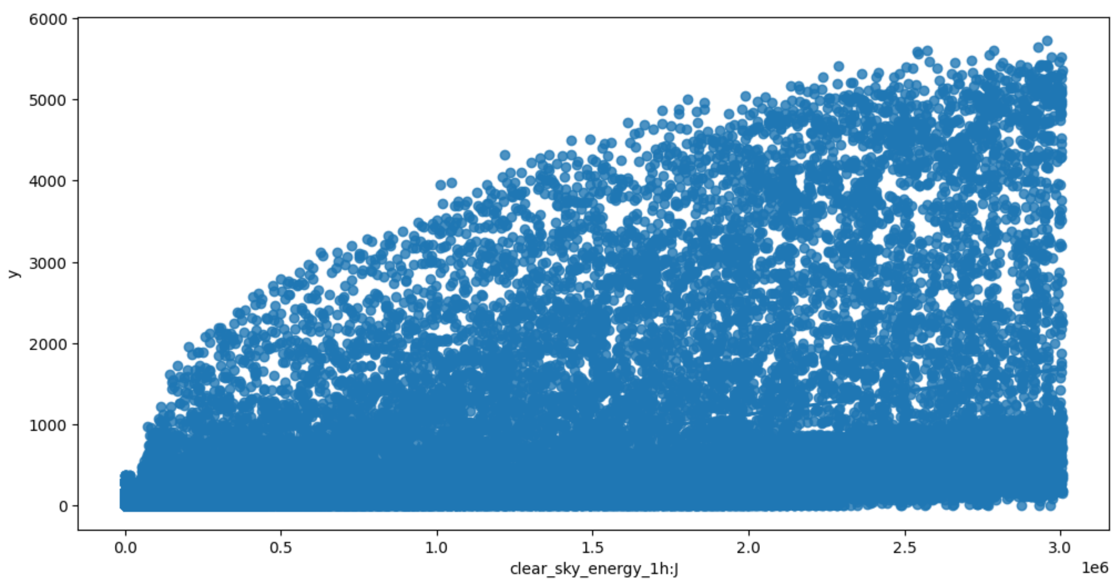
**`train_data` - spearman correlation matrix; focus: absolute correlation for `y` >= `0.5`**



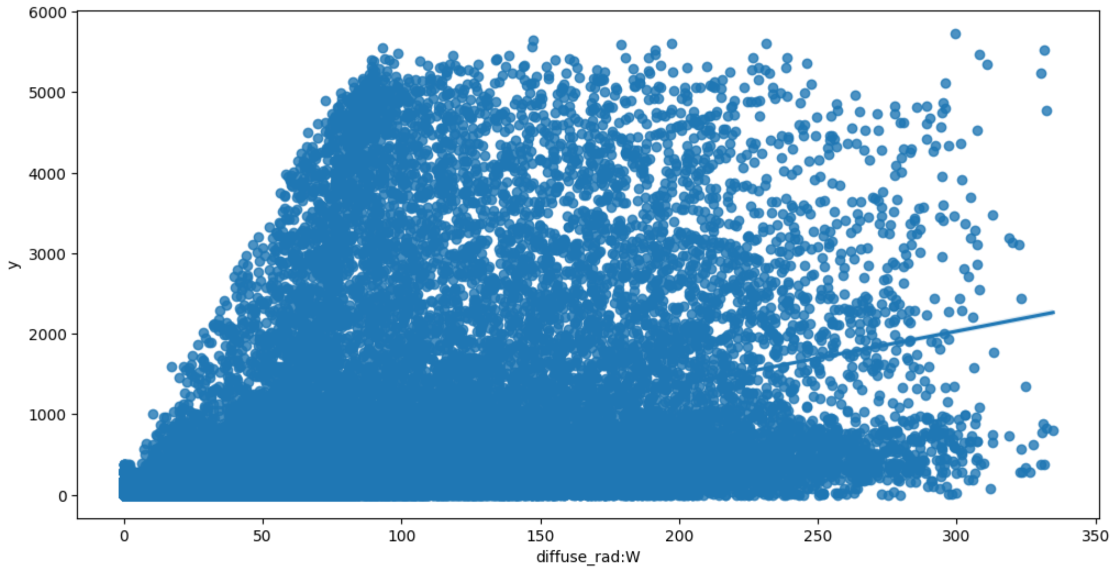

**Feature interaction between `clear_sky_rad:W`/`y` in `train_data`**



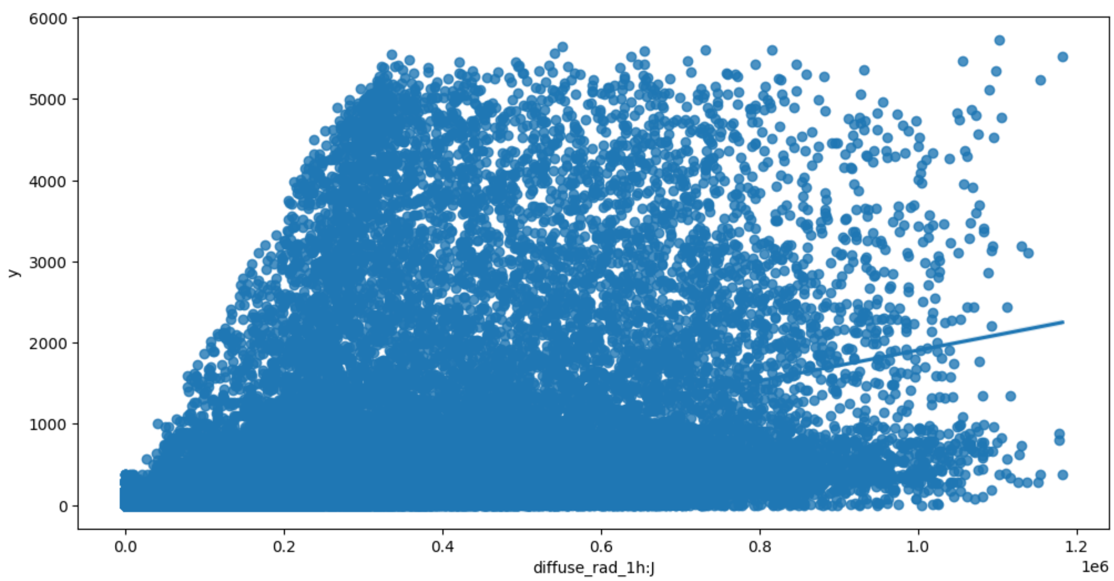

**Feature interaction between `clear_sky_energy_1h:J/y` in `train_data`**



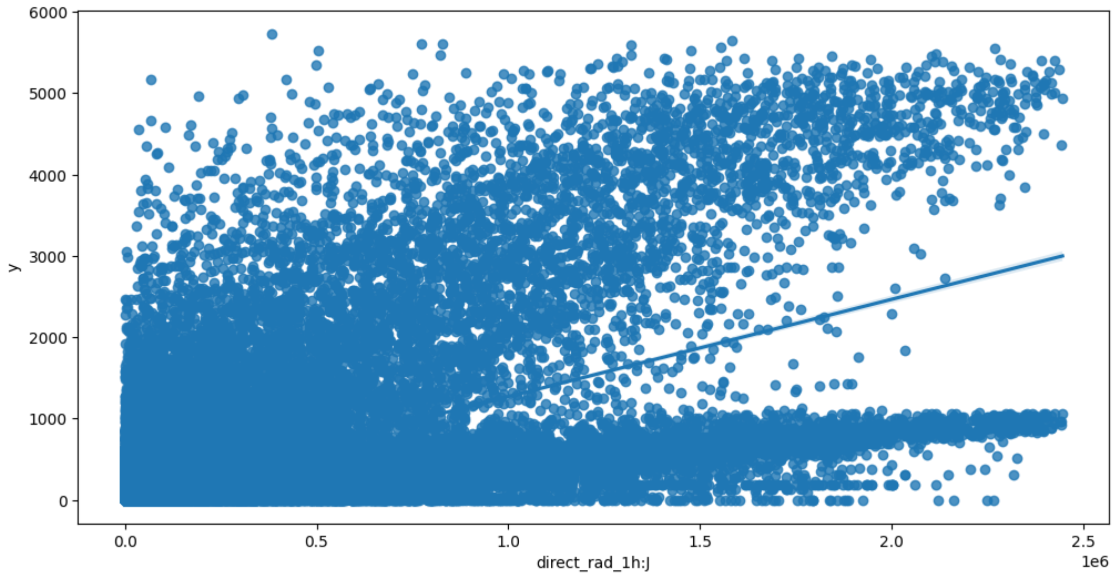

**Feature interaction between `diffuse_rad:W/y` in `train_data`**



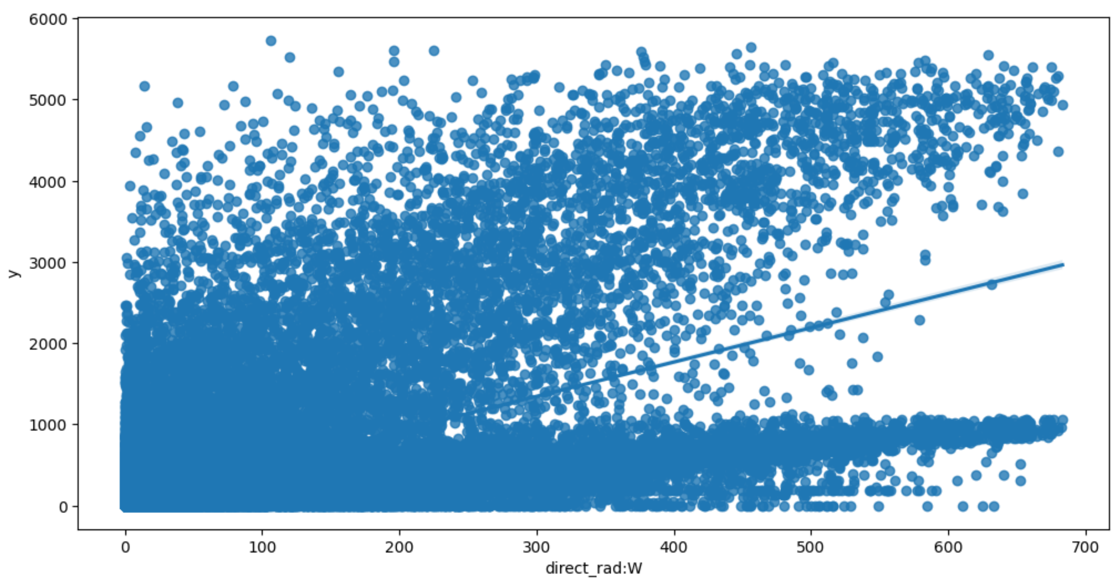

**Feature interaction between `diffuse_rad_1h:J`/`y` in `train_data`**



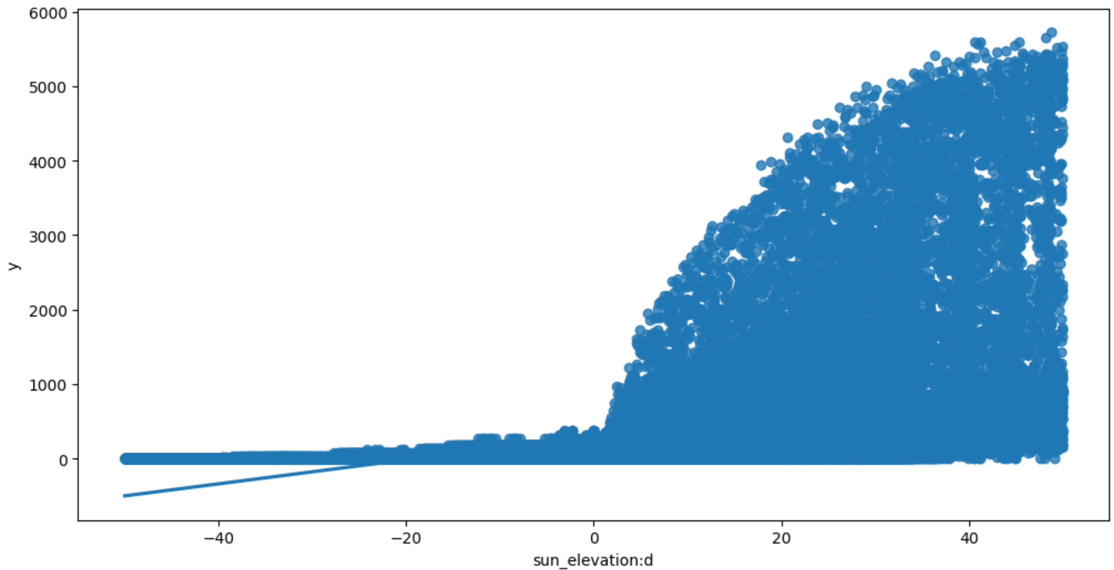

**Feature interaction between `direct_rad_1h:J`/`y` in `train_data`**



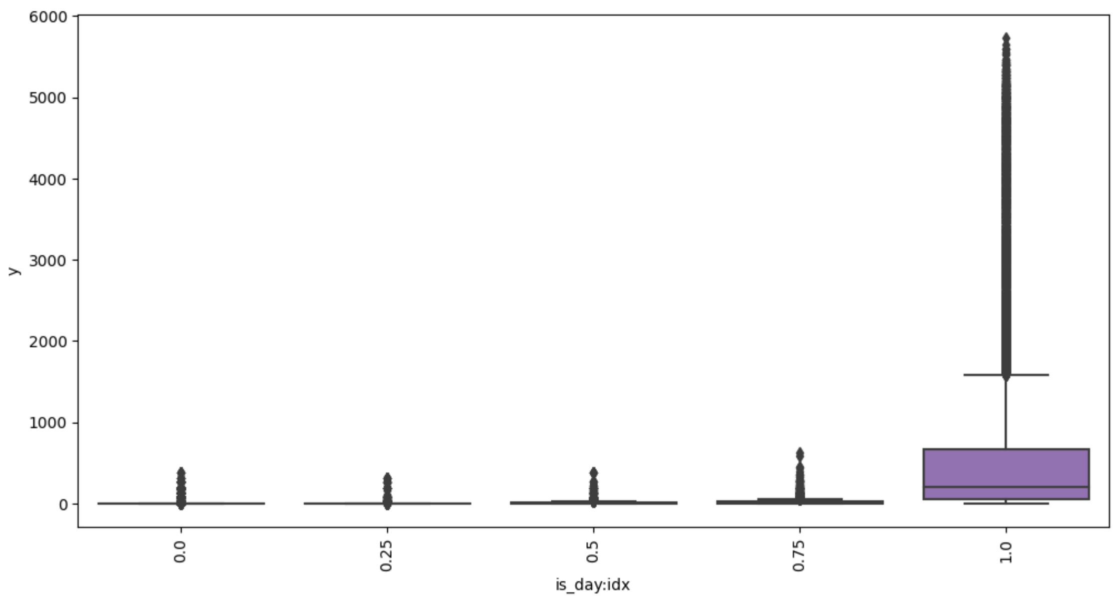

**Feature interaction between `direct_rad:W/y` in `train_data`**



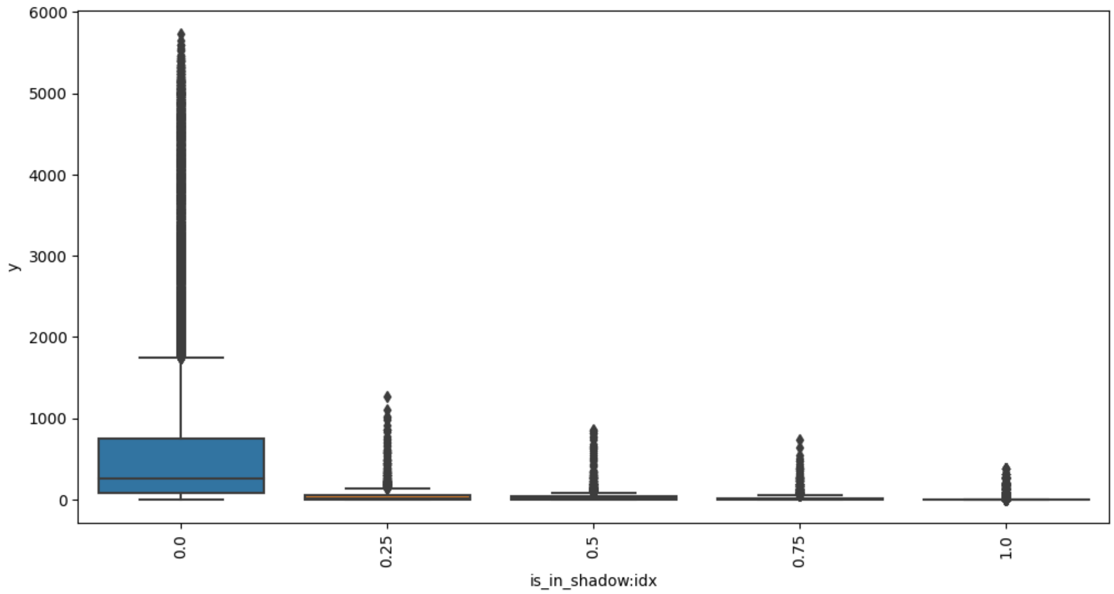

**Feature interaction between `sun_elevation:d/y` in `train_data`**




**Feature interaction between `is_day:idx/y` in `train_data`**




**Feature interaction between `is_in_shadow:idx/y` in `train_data`**




## 2 Starting

[8]:
```
import os


# Get the last submission number
last_submission_number = int(max([int(filename.split('_')[1].split('.')[0]) for␣
↪filename in os.listdir('submissions') if "submission" in filename]))
print("Last submission number:", last_submission_number)
print("Now creating submission number:", last_submission_number + 1)

# Create the new filename
new_filename = f'submission_{last_submission_number + 1}'

hello = os.environ.get('HELLO')
if hello is not None:
    new_filename += f'_{hello}'

print("New filename:", new_filename)
```

```
Last submission number: 95
Now creating submission number: 96
New filename: submission_96
```

[9]:
```
predictors = [None, None, None]
```

[10]:

```python
def fit_predictor_for_location(loc):
    print(f"Training model for location {loc}...")
    # sum of sample weights for this location, and number of rows, for both␣
↪train and tune data and test data
    if weight_evaluation:
        print("Train data sample weight sum:",␣
↪train_data[train_data["location"] == loc]["sample_weight"].sum())
        print("Train data number of rows:", train_data[train_data["location"]␣
↪== loc].shape[0])
        if use_tune_data:
            print("Tune data sample weight sum:",␣
↪tuning_data[tuning_data["location"] == loc]["sample_weight"].sum())
            print("Tune data number of rows:",␣
↪tuning_data[tuning_data["location"] == loc].shape[0])
        if use_test_data:
            print("Test data sample weight sum:",␣
↪test_data[test_data["location"] == loc]["sample_weight"].sum())
            print("Test data number of rows:", test_data[test_data["location"]␣
↪== loc].shape[0])
    predictor = TabularPredictor(
        label=label,
        eval_metric=metric,
        path=f"AutogluonModels/{new_filename}_{loc}",
        # sample_weight=sample_weight,
        # weight_evaluation=weight_evaluation,
        # groups="group" if use_groups else None,
    ).fit(
        train_data=train_data[train_data["location"] == loc].
↪drop(columns=["ds"]),
        time_limit=time_limit,
        # presets=presets,
        num_stack_levels=num_stack_levels,
        num_bag_folds=num_bag_folds if not use_groups else 2,# just put␣
↪somethin, will be overwritten anyways
        num_bag_sets=num_bag_sets,
        tuning_data=tuning_data[tuning_data["location"] == loc].
↪reset_index(drop=True).drop(columns=["ds"]) if use_tune_data else None,
        use_bag_holdout=use_bag_holdout,
        # holdout_frac=holdout_frac,
    )

    # evaluate on test data
    if use_test_data:
        # drop sample_weight column
        t = test_data[test_data["location"] == loc]#.
↪drop(columns=["sample_weight"])
```

```python
        perf = predictor.evaluate(t)
        print("Evaluation on test data:")
        print(perf[predictor.eval_metric.name])

    return predictor

loc = "A"
predictors[0] = fit_predictor_for_location(loc)
```

```
Beginning AutoGluon training … Time limit = 1800s
AutoGluon will save models to "AutogluonModels/submission_96_A/"
AutoGluon Version:  0.8.2
Python Version:     3.10.12
Operating System:   Linux
Platform Machine:   x86_64
Platform Version:   #1 SMP Debian 5.10.197-1 (2023-09-29)
Disk Space Avail:   213.35 GB / 315.93 GB (67.5%)
Train Data Rows:    31872
Train Data Columns: 34
Tuning Data Rows:    1093
Tuning Data Columns: 34
Label Column: y
Preprocessing data …
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and many unique label-values observed).
        Label info (max, min, mean, stddev): (5733.42, 0.0, 649.68162,
1178.37671)
        If 'regression' is not the correct problem_type, please manually specify
the problem_type parameter during predictor init (You may specify problem_type
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    131870.2 MB
        Train Data (Original)  Memory Usage: 10.61 MB (0.0% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 1 features to boolean dtype as they
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…
        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…
```

```
Training model for location A…
        Useless Original Features (Count: 2): ['elevation:m', 'location']
                These features carry no predictive signal and should be manually
investigated.
                This is typically a feature which has the same value for all
rows.
                These features do not need to be present at inference time.
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 29 | ['ceiling_height_agl:m',
'clear_sky_energy_1h:J', 'clear_sky_rad:W', 'cloud_base_agl:m', 'diffuse_rad:W',
…]
                ('int', [])   :  3 | ['is_estimated', 'hour', 'year']
        Types of features in processed data (raw dtype, special dtypes):
                ('float', [])     : 29 | ['ceiling_height_agl:m',
'clear_sky_energy_1h:J', 'clear_sky_rad:W', 'cloud_base_agl:m', 'diffuse_rad:W',
…]
                ('int', [])       :  2 | ['hour', 'year']
                ('int', ['bool']) :  1 | ['is_estimated']
        0.1s = Fit runtime
        32 features in original data used to generate 32 features in processed
data.
        Train Data (Processed) Memory Usage: 8.21 MB (0.0% of available memory)
Data preprocessing and feature engineering runtime = 0.17s …
AutoGluon will gauge predictive performance using evaluation metric:
'mean_absolute_error'
        This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
        To change this, specify the eval_metric parameter of Predictor()
use_bag_holdout=True, will use tuning_data as holdout (will not be used for
early stopping).
User-specified model hyperparameters to be fit:
{
        'NN_TORCH': {},
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
'GBMLarge'],
        'CAT': {},
        'XGB': {},
        'FASTAI': {},
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
```

```
'problem_types': ['regression', 'quantile']}}],
        'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}
Fitting 11 L1 models …
Fitting model: KNeighborsUnif_BAG_L1 … Training model for up to 1799.83s of
the 1799.83s of remaining time.
        -140.7608        = Validation score   (-mean_absolute_error)
        0.03s    = Training   runtime
        0.38s    = Validation runtime
Fitting model: KNeighborsDist_BAG_L1 … Training model for up to 1799.11s of
the 1799.11s of remaining time.
        -140.9566        = Validation score   (-mean_absolute_error)
        0.03s    = Training   runtime
        0.4s     = Validation runtime
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 1798.62s of the
1798.61s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -92.5916         = Validation score   (-mean_absolute_error)
        28.8s    = Training   runtime
        17.06s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 1759.94s of the
1759.94s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -95.843  = Validation score   (-mean_absolute_error)
        24.6s    = Training   runtime
        7.22s    = Validation runtime
Fitting model: RandomForestMSE_BAG_L1 … Training model for up to 1731.24s of
the 1731.23s of remaining time.
        -108.2786        = Validation score   (-mean_absolute_error)
        8.28s    = Training   runtime
        1.2s     = Validation runtime
Fitting model: CatBoost_BAG_L1 … Training model for up to 1720.54s of the
1720.54s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -103.3862        = Validation score   (-mean_absolute_error)
        189.07s  = Training   runtime
        0.09s    = Validation runtime
Fitting model: ExtraTreesMSE_BAG_L1 … Training model for up to 1530.31s of the
1530.3s of remaining time.
        -111.9213        = Validation score   (-mean_absolute_error)
        1.74s    = Training   runtime
        1.2s     = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L1 … Training model for up to 1526.15s of
the 1526.15s of remaining time.
```

```
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -107.2384        = Validation score   (-mean_absolute_error)
        38.19s   = Training   runtime
        0.47s    = Validation runtime
Fitting model: XGBoost_BAG_L1 … Training model for up to 1486.22s of the
1486.21s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -101.7946        = Validation score   (-mean_absolute_error)
        13.08s   = Training   runtime
        0.51s    = Validation runtime
Fitting model: NeuralNetTorch_BAG_L1 … Training model for up to 1470.88s of
the 1470.88s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -86.9395         = Validation score   (-mean_absolute_error)
        112.67s  = Training   runtime
        0.3s     = Validation runtime
Fitting model: LightGBMLarge_BAG_L1 … Training model for up to 1356.81s of the
1356.81s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -94.8567         = Validation score   (-mean_absolute_error)
        94.53s   = Training   runtime
        26.81s   = Validation runtime
Repeating k-fold bagging: 2/20
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 1250.29s of the
1250.29s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -92.6033         = Validation score   (-mean_absolute_error)
        58.16s   = Training   runtime
        39.56s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 1213.46s of the
1213.46s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -95.7537         = Validation score   (-mean_absolute_error)
        48.63s   = Training   runtime
        11.28s   = Validation runtime
Fitting model: CatBoost_BAG_L1 … Training model for up to 1185.16s of the
1185.16s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -103.2615        = Validation score   (-mean_absolute_error)
        380.47s  = Training   runtime
        0.18s    = Validation runtime
```

```
Fitting model: NeuralNetFastAI_BAG_L1 … Training model for up to 992.38s of
the 992.38s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -107.9135        = Validation score   (-mean_absolute_error)
        76.8s    = Training   runtime
        0.93s    = Validation runtime
Fitting model: XGBoost_BAG_L1 … Training model for up to 951.37s of the
951.36s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -101.4482        = Validation score   (-mean_absolute_error)
        23.55s   = Training   runtime
        0.89s    = Validation runtime
Fitting model: NeuralNetTorch_BAG_L1 … Training model for up to 939.29s of the
939.29s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -86.5488         = Validation score   (-mean_absolute_error)
        229.71s  = Training   runtime
        0.63s    = Validation runtime
Fitting model: LightGBMLarge_BAG_L1 … Training model for up to 820.72s of the
820.72s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -94.2604         = Validation score   (-mean_absolute_error)
        189.14s  = Training   runtime
        47.42s   = Validation runtime
Completed 2/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L2 … Training model for up to 360.0s of the
711.91s of remaining time.
        -85.6831         = Validation score   (-mean_absolute_error)
        0.42s    = Training   runtime
        0.0s     = Validation runtime
AutoGluon training complete, total runtime = 1088.53s … Best model:
"WeightedEnsemble_L2"
TabularPredictor saved. To load, use: predictor =
TabularPredictor.load("AutogluonModels/submission_96_A/")
Evaluation: mean_absolute_error on test data: -91.38656916356734
        Note: Scores are always higher_is_better. This metric score can be
multiplied by -1 to get the metric value.
Evaluations on test data:
{
    "mean_absolute_error": -91.38656916356734,
    "root_mean_squared_error": -314.3477051569919,
    "mean_squared_error": -98814.47973746709,
    "r2": 0.8946273600380232,
    "pearsonr": 0.9469860621779503,
```

```
    "median_absolute_error": -1.3219637870788574
}
```

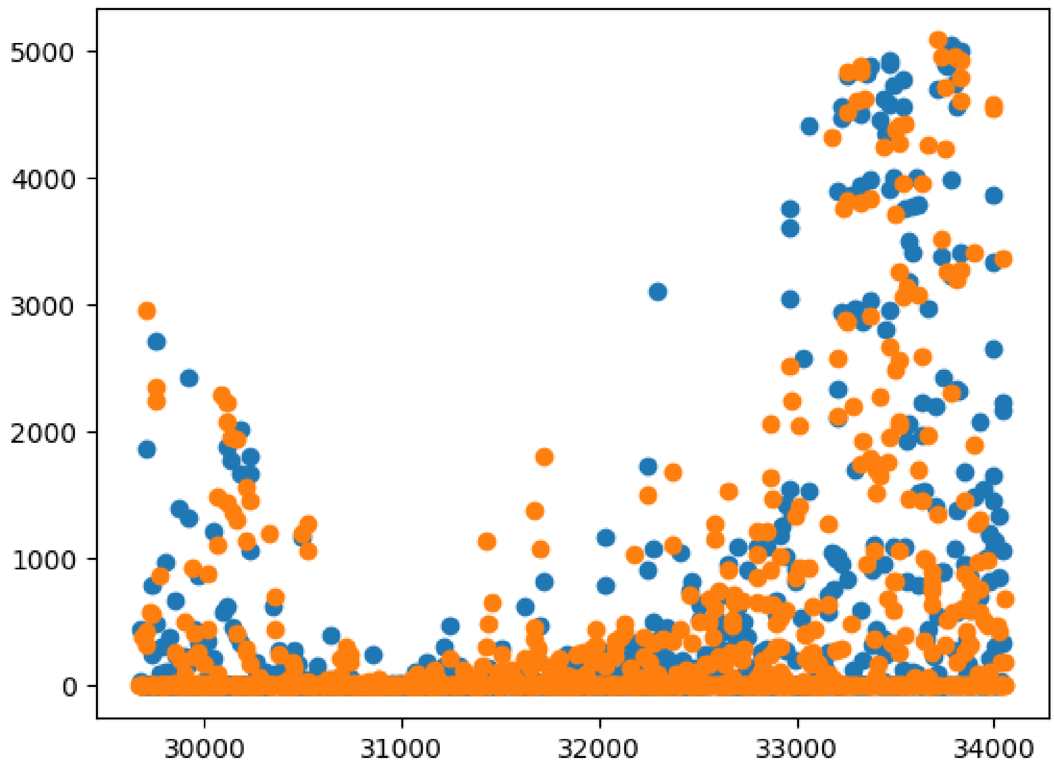
```
Evaluation on test data:
-91.38656916356734
```

[11]:

```python
import matplotlib.pyplot as plt

leaderboards = [None, None, None]
def leaderboard_for_location(i, loc):
    if use_test_data:
        lb = predictors[i].leaderboard(test_data[test_data["location"] == loc])
        lb["location"] = loc
        plt.scatter(test_data[test_data["location"] == loc]["y"].index,␣
 ↪test_data[test_data["location"] == loc]["y"])
        if use_tune_data:
            plt.scatter(tuning_data[tuning_data["location"] == loc]["y"].index,␣
 ↪tuning_data[tuning_data["location"] == loc]["y"])
        plt.show()

        return lb
    else:
        return pd.DataFrame()

leaderboards[0] = leaderboard_for_location(0, loc)
```

```
                     model  score_test   score_val  pred_time_test
pred_time_val    fit_time  pred_time_test_marginal  pred_time_val_marginal
fit_time_marginal  stack_level  can_infer  fit_order
0      WeightedEnsemble_L2  -91.386569  -85.683123        3.000079
40.194988  288.281092                 0.003309                0.000674
0.418749            2       True         12
1        LightGBMXT_BAG_L1  -93.124416  -92.603287        2.613239
39.563026   58.155759                 2.613239               39.563026
58.155759            1       True          3
2     LightGBMLarge_BAG_L1  -94.537043  -94.260380        7.344643
47.419793  189.143018                 7.344643               47.419793
189.143018            1       True         11
3    NeuralNetTorch_BAG_L1  -94.574389  -86.548840        0.383532
0.631288  229.706584                 0.383532                0.631288
229.706584            1       True         10
4          LightGBM_BAG_L1  -96.718877  -95.753749        1.501362
11.281142   48.632016                 1.501362               11.281142
48.632016            1       True          4
5          CatBoost_BAG_L1 -101.025488 -103.261487        0.141366
0.182645  380.473184                 0.141366                0.182645
380.473184            1       True          6
6   RandomForestMSE_BAG_L1 -101.818436 -108.278639        0.588561
```

```
1.204999    8.276278                  0.588561                1.204999
8.276278            1       True          5
7      ExtraTreesMSE_BAG_L1 -103.820493 -111.921296        0.605485
1.198890    1.739662                  0.605485                1.198890
1.739662            1       True          7
8               XGBoost_BAG_L1 -103.905230 -101.448236        0.339590
0.894776   23.548844                  0.339590                0.894776
23.548844            1       True          9
9    NeuralNetFastAI_BAG_L1 -106.185664 -107.913464        1.093756
0.929719   76.798589                  1.093756                0.929719
76.798589            1       True          8
10    KNeighborsDist_BAG_L1 -124.177233 -140.956611        0.019751
0.397748    0.032993                  0.019751                0.397748
0.032993            1       True          2
11    KNeighborsUnif_BAG_L1 -124.918514 -140.760811        0.193960
0.381145    0.031478                  0.193960                0.381145
0.031478            1       True          1
```




[12]:
```
loc = "B"
predictors[1] = fit_predictor_for_location(loc)
leaderboards[1] = leaderboard_for_location(1, loc)
```

```
Beginning AutoGluon training … Time limit = 1800s
```

```
AutoGluon will save models to "AutogluonModels/submission_96_B/"
AutoGluon Version:  0.8.2
Python Version:     3.10.12
Operating System:   Linux
Platform Machine:   x86_64
Platform Version:   #1 SMP Debian 5.10.197-1 (2023-09-29)
Disk Space Avail:   209.65 GB / 315.93 GB (66.4%)
Train Data Rows:    31020
Train Data Columns: 34
Tuning Data Rows:    898
Tuning Data Columns: 34
Label Column: y
Preprocessing data …
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and many unique label-values observed).
        Label info (max, min, mean, stddev): (1152.3, -0.0, 99.56591, 196.469)
        If 'regression' is not the correct problem_type, please manually specify
the problem_type parameter during predictor init (You may specify problem_type
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    130041.11 MB
        Train Data (Original)  Memory Usage: 10.28 MB (0.0% of available memory)

Training model for location B…

        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 1 features to boolean dtype as they
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…
        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…
        Useless Original Features (Count: 2): ['elevation:m', 'location']
                These features carry no predictive signal and should be manually
investigated.
                This is typically a feature which has the same value for all
rows.
                These features do not need to be present at inference time.
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 29 | ['ceiling_height_agl:m',
'clear_sky_energy_1h:J', 'clear_sky_rad:W', 'cloud_base_agl:m', 'diffuse_rad:W',
```

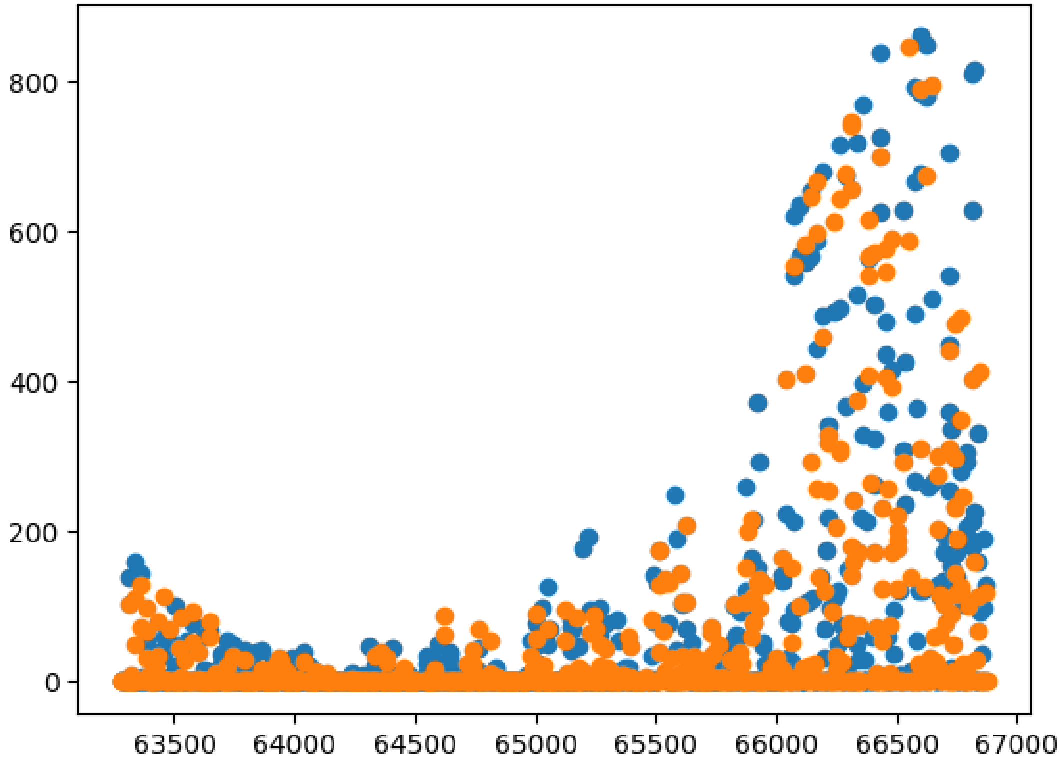
```
…]
                ('int', [])   :  3 | ['is_estimated', 'hour', 'year']
        Types of features in processed data (raw dtype, special dtypes):
                ('float', [])     : 29 | ['ceiling_height_agl:m',
'clear_sky_energy_1h:J', 'clear_sky_rad:W', 'cloud_base_agl:m', 'diffuse_rad:W',
…]
                ('int', [])       :  2 | ['hour', 'year']
                ('int', ['bool']) :  1 | ['is_estimated']
        0.1s = Fit runtime
        32 features in original data used to generate 32 features in processed
data.
        Train Data (Processed) Memory Usage: 7.95 MB (0.0% of available memory)
Data preprocessing and feature engineering runtime = 0.17s …
AutoGluon will gauge predictive performance using evaluation metric:
'mean_absolute_error'
        This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
        To change this, specify the eval_metric parameter of Predictor()
use_bag_holdout=True, will use tuning_data as holdout (will not be used for
early stopping).
User-specified model hyperparameters to be fit:
{
        'NN_TORCH': {},
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
'GBMLarge'],
        'CAT': {},
        'XGB': {},
        'FASTAI': {},
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}
Fitting 11 L1 models …
Fitting model: KNeighborsUnif_BAG_L1 … Training model for up to 1799.83s of
the 1799.83s of remaining time.
        -23.6782         = Validation score   (-mean_absolute_error)
        0.03s    = Training   runtime
        0.42s    = Validation runtime
Fitting model: KNeighborsDist_BAG_L1 … Training model for up to 1799.32s of
```

```
the 1799.32s of remaining time.
        -23.6489         = Validation score   (-mean_absolute_error)
        0.03s    = Training   runtime
        0.41s    = Validation runtime
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 1798.8s of the
1798.8s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -14.4523         = Validation score   (-mean_absolute_error)
        28.56s   = Training   runtime
        18.37s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 1764.38s of the
1764.37s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -14.2832         = Validation score   (-mean_absolute_error)
        30.02s   = Training   runtime
        18.38s   = Validation runtime
Fitting model: RandomForestMSE_BAG_L1 … Training model for up to 1728.8s of
the 1728.8s of remaining time.
        -14.8681         = Validation score   (-mean_absolute_error)
        8.88s    = Training   runtime
        1.07s    = Validation runtime
Fitting model: CatBoost_BAG_L1 … Training model for up to 1717.84s of the
1717.84s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -15.9903         = Validation score   (-mean_absolute_error)
        192.97s  = Training   runtime
        0.11s    = Validation runtime
Fitting model: ExtraTreesMSE_BAG_L1 … Training model for up to 1523.59s of the
1523.59s of remaining time.
        -13.8493         = Validation score   (-mean_absolute_error)
        1.56s    = Training   runtime
        1.06s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L1 … Training model for up to 1519.9s of
the 1519.9s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.9749         = Validation score   (-mean_absolute_error)
        37.9s    = Training   runtime
        0.48s    = Validation runtime
Fitting model: XGBoost_BAG_L1 … Training model for up to 1480.24s of the
1480.24s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -14.852  = Validation score   (-mean_absolute_error)
        84.55s   = Training   runtime
```

```
        24.94s   = Validation runtime
Fitting model: NeuralNetTorch_BAG_L1 … Training model for up to 1390.49s of
the 1390.49s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -11.6634         = Validation score   (-mean_absolute_error)
        141.09s  = Training   runtime
        0.31s    = Validation runtime
Fitting model: LightGBMLarge_BAG_L1 … Training model for up to 1248.01s of the
1248.0s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.492  = Validation score   (-mean_absolute_error)
        94.06s   = Training   runtime
        21.93s   = Validation runtime
Repeating k-fold bagging: 2/20
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 1144.13s of the
1144.13s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -14.2934         = Validation score   (-mean_absolute_error)
        58.21s   = Training   runtime
        34.22s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 1107.92s of the
1107.92s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -14.2042         = Validation score   (-mean_absolute_error)
        60.9s    = Training   runtime
        36.22s   = Validation runtime
Fitting model: CatBoost_BAG_L1 … Training model for up to 1070.96s of the
1070.96s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -15.8748         = Validation score   (-mean_absolute_error)
        386.36s  = Training   runtime
        0.21s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L1 … Training model for up to 876.26s of
the 876.26s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -14.001  = Validation score   (-mean_absolute_error)
        76.39s   = Training   runtime
        0.94s    = Validation runtime
Fitting model: XGBoost_BAG_L1 … Training model for up to 835.4s of the 835.4s
of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
```

```
        -14.6354         = Validation score   (-mean_absolute_error)
        168.32s  = Training   runtime
        46.84s   = Validation runtime
Fitting model: NeuralNetTorch_BAG_L1 … Training model for up to 744.26s of the
744.26s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -11.6064         = Validation score   (-mean_absolute_error)
        291.11s  = Training   runtime
        0.63s    = Validation runtime
Fitting model: LightGBMLarge_BAG_L1 … Training model for up to 592.71s of the
592.71s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.3677         = Validation score   (-mean_absolute_error)
        189.73s  = Training   runtime
        45.02s   = Validation runtime
Completed 2/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L2 … Training model for up to 360.0s of the
484.26s of remaining time.
        -11.3969         = Validation score   (-mean_absolute_error)
        0.41s    = Training   runtime
        0.0s     = Validation runtime
AutoGluon training complete, total runtime = 1316.25s … Best model:
"WeightedEnsemble_L2"
TabularPredictor saved. To load, use: predictor =
TabularPredictor.load("AutogluonModels/submission_96_B/")
Evaluation: mean_absolute_error on test data: -13.82015574286899
        Note: Scores are always higher_is_better. This metric score can be
multiplied by -1 to get the metric value.
Evaluations on test data:
{
    "mean_absolute_error": -13.82015574286899,
    "root_mean_squared_error": -43.61744319903937,
    "mean_squared_error": -1902.4813512214262,
    "r2": 0.9139982536577307,
    "pearsonr": 0.9568816029552053,
    "median_absolute_error": -0.3668253384183716
}

Evaluation on test data:
-13.82015574286899
                     model  score_test  score_val  pred_time_test  pred_time_val
fit_time  pred_time_test_marginal  pred_time_val_marginal  fit_time_marginal
stack_level  can_infer  fit_order
0    NeuralNetTorch_BAG_L1  -13.779852 -11.606354        0.370063       0.632516
291.110906                0.370063                0.632516         291.110906
1       True         10
```

```
1       WeightedEnsemble_L2  -13.820156 -11.396950        3.495752      35.908665
351.293035                0.003501                0.000581          0.407487
2       True          12
2      LightGBMLarge_BAG_L1  -15.759067 -13.367725        7.403612      45.024767
189.730639                7.403612               45.024767        189.730639
1       True          11
3    NeuralNetFastAI_BAG_L1  -16.618762 -14.000956        0.989892       0.943059
76.389157                0.989892               0.943059         76.389157
1       True          8
4           LightGBM_BAG_L1  -16.866271 -14.204224        2.615975      36.218588
60.897540                2.615975               36.218588        60.897540
1       True          4
5      ExtraTreesMSE_BAG_L1  -17.325265 -13.849344        0.521476       1.056313
1.563362                0.521476                1.056313          1.563362
1       True          7
6            XGBoost_BAG_L1  -17.385425 -14.635356        4.389942      46.841645
168.321279                4.389942               46.841645        168.321279
1       True          9
7         LightGBMXT_BAG_L1  -17.534210 -14.293414        2.600712      34.219255
58.211280                2.600712               34.219255        58.211280
1       True          3
8           CatBoost_BAG_L1  -18.010877 -15.874789        0.140189       0.210378
386.362599                0.140189                0.210378        386.362599
1       True          6
9    RandomForestMSE_BAG_L1  -18.510659 -14.868143        0.485080       1.065722
8.884482                0.485080                1.065722          8.884482
1       True          5
10   KNeighborsDist_BAG_L1  -30.061916 -23.648941        0.020382       0.410346
0.032739                0.020382                0.410346          0.032739
1       True          2
11   KNeighborsUnif_BAG_L1  -30.091156 -23.678158        0.017780       0.416663
0.032354                0.017780                0.416663          0.032354
1       True          1
```




[13]:
```
loc = "C"
predictors[2] = fit_predictor_for_location(loc)
leaderboards[2] = leaderboard_for_location(2, loc)
```

```
Beginning AutoGluon training … Time limit = 1800s
AutoGluon will save models to "AutogluonModels/submission_96_C/"
AutoGluon Version:  0.8.2
Python Version:     3.10.12
Operating System:   Linux
Platform Machine:   x86_64
Platform Version:   #1 SMP Debian 5.10.197-1 (2023-09-29)
Disk Space Avail:   205.17 GB / 315.93 GB (64.9%)
Train Data Rows:    24594
Train Data Columns: 34
Tuning Data Rows:    737
Tuning Data Columns: 34
Label Column: y
Preprocessing data …
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and label-values can't be converted to int).
        Label info (max, min, mean, stddev): (999.6, -0.0, 79.8926, 168.407)
        If 'regression' is not the correct problem_type, please manually specify
```

```
the problem_type parameter during predictor init (You may specify problem_type
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…

Training model for location C…

        Available Memory:                    129886.6 MB
        Train Data (Original)  Memory Usage: 8.16 MB (0.0% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 1 features to boolean dtype as they
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…
        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…
        Useless Original Features (Count: 2): ['elevation:m', 'location']
                These features carry no predictive signal and should be manually
investigated.
                This is typically a feature which has the same value for all
rows.
                These features do not need to be present at inference time.
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 29 | ['ceiling_height_agl:m',
'clear_sky_energy_1h:J', 'clear_sky_rad:W', 'cloud_base_agl:m', 'diffuse_rad:W',
…]
                ('int', [])   :  3 | ['is_estimated', 'hour', 'year']
        Types of features in processed data (raw dtype, special dtypes):
                ('float', [])     : 29 | ['ceiling_height_agl:m',
'clear_sky_energy_1h:J', 'clear_sky_rad:W', 'cloud_base_agl:m', 'diffuse_rad:W',
…]
                ('int', [])       :  2 | ['hour', 'year']
                ('int', ['bool']) :  1 | ['is_estimated']
        0.1s = Fit runtime
        32 features in original data used to generate 32 features in processed
data.
        Train Data (Processed) Memory Usage: 6.31 MB (0.0% of available memory)
Data preprocessing and feature engineering runtime = 0.14s …
AutoGluon will gauge predictive performance using evaluation metric:
'mean_absolute_error'
        This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
```

```
        To change this, specify the eval_metric parameter of Predictor()
use_bag_holdout=True, will use tuning_data as holdout (will not be used for
early stopping).
User-specified model hyperparameters to be fit:
{
        'NN_TORCH': {},
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
'GBMLarge'],
        'CAT': {},
        'XGB': {},
        'FASTAI': {},
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}
Fitting 11 L1 models …
Fitting model: KNeighborsUnif_BAG_L1 … Training model for up to 1799.86s of
the 1799.85s of remaining time.
        -23.6472         = Validation score   (-mean_absolute_error)
        0.02s    = Training   runtime
        2.42s    = Validation runtime
Fitting model: KNeighborsDist_BAG_L1 … Training model for up to 1797.2s of the
1797.2s of remaining time.
        -23.6995         = Validation score   (-mean_absolute_error)
        0.02s    = Training   runtime
        0.27s    = Validation runtime
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 1796.85s of the
1796.85s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -11.8495         = Validation score   (-mean_absolute_error)
        26.77s   = Training   runtime
        12.3s    = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 1765.47s of the
1765.47s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.4321         = Validation score   (-mean_absolute_error)
        24.04s   = Training   runtime
```

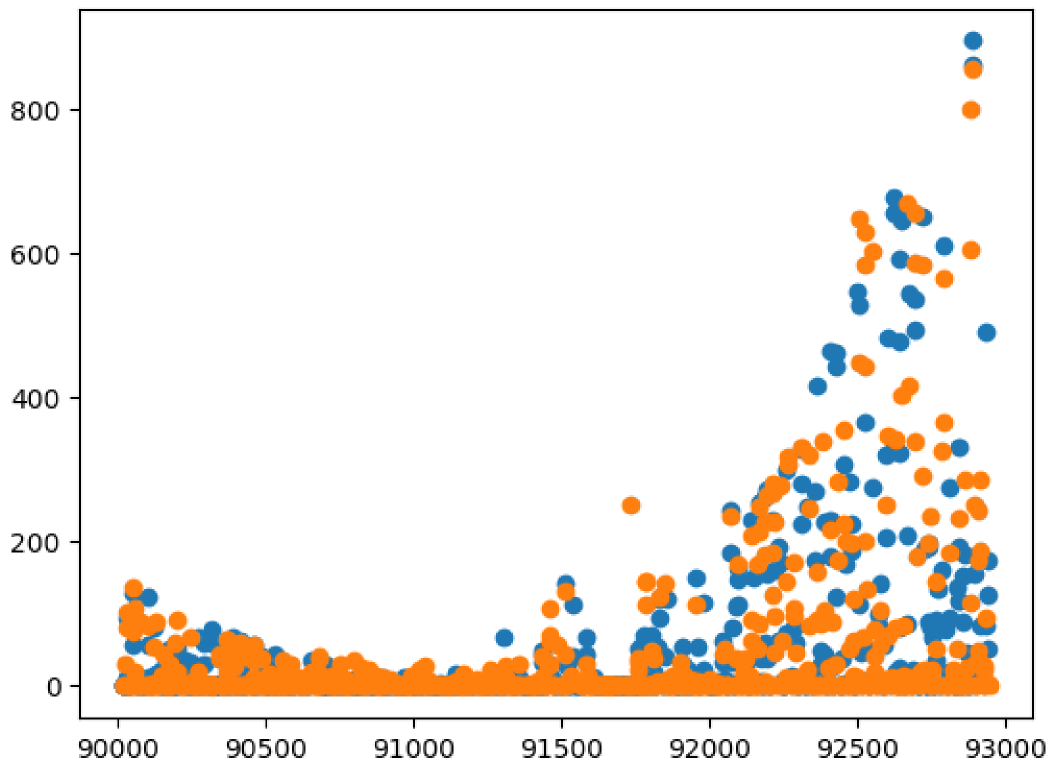
```
        5.42s    = Validation runtime
Fitting model: RandomForestMSE_BAG_L1 … Training model for up to 1738.12s of
the 1738.12s of remaining time.
        -16.3363         = Validation score   (-mean_absolute_error)
        4.86s    = Training   runtime
        0.73s    = Validation runtime
Fitting model: CatBoost_BAG_L1 … Training model for up to 1731.92s of the
1731.91s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.0045         = Validation score   (-mean_absolute_error)
        186.38s  = Training   runtime
        0.09s    = Validation runtime
Fitting model: ExtraTreesMSE_BAG_L1 … Training model for up to 1544.31s of the
1544.3s of remaining time.
        -15.9433         = Validation score   (-mean_absolute_error)
        1.02s    = Training   runtime
        0.74s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L1 … Training model for up to 1541.87s of
the 1541.87s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -14.3155         = Validation score   (-mean_absolute_error)
        31.17s   = Training   runtime
        0.39s    = Validation runtime
Fitting model: XGBoost_BAG_L1 … Training model for up to 1509.05s of the
1509.05s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.4046         = Validation score   (-mean_absolute_error)
        60.6s    = Training   runtime
        5.93s    = Validation runtime
Fitting model: NeuralNetTorch_BAG_L1 … Training model for up to 1444.7s of the
1444.7s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.4402         = Validation score   (-mean_absolute_error)
        67.95s   = Training   runtime
        0.27s    = Validation runtime
Fitting model: LightGBMLarge_BAG_L1 … Training model for up to 1375.42s of the
1375.42s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -12.7665         = Validation score   (-mean_absolute_error)
        88.98s   = Training   runtime
        11.73s   = Validation runtime
Repeating k-fold bagging: 2/20
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 1277.91s of the
```

```
1277.91s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -11.764  = Validation score   (-mean_absolute_error)
        54.47s   = Training   runtime
        26.49s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 1244.69s of the
1244.69s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.2485         = Validation score   (-mean_absolute_error)
        48.09s   = Training   runtime
        9.61s    = Validation runtime
Fitting model: CatBoost_BAG_L1 … Training model for up to 1216.44s of the
1216.44s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -12.881  = Validation score   (-mean_absolute_error)
        372.49s  = Training   runtime
        0.18s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L1 … Training model for up to 1029.01s of
the 1029.01s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -14.412  = Validation score   (-mean_absolute_error)
        61.89s   = Training   runtime
        0.8s     = Validation runtime
Fitting model: XGBoost_BAG_L1 … Training model for up to 996.19s of the
996.19s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.4943         = Validation score   (-mean_absolute_error)
        103.47s  = Training   runtime
        8.18s    = Validation runtime
Fitting model: NeuralNetTorch_BAG_L1 … Training model for up to 948.87s of the
948.87s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.5101         = Validation score   (-mean_absolute_error)
        143.16s  = Training   runtime
        0.65s    = Validation runtime
Fitting model: LightGBMLarge_BAG_L1 … Training model for up to 872.07s of the
872.07s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -12.6783         = Validation score   (-mean_absolute_error)
        179.54s  = Training   runtime
        21.83s   = Validation runtime
```

```
Repeating k-fold bagging: 3/20
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 770.6s of the
770.6s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -11.7186         = Validation score   (-mean_absolute_error)
        80.9s    = Training   runtime
        36.63s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 737.15s of the
737.15s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.214  = Validation score   (-mean_absolute_error)
        71.74s   = Training   runtime
        13.76s   = Validation runtime
Fitting model: CatBoost_BAG_L1 … Training model for up to 708.66s of the
708.66s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -12.7833         = Validation score   (-mean_absolute_error)
        559.36s  = Training   runtime
        0.26s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L1 … Training model for up to 520.43s of
the 520.43s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -14.457  = Validation score   (-mean_absolute_error)
        93.04s   = Training   runtime
        1.2s     = Validation runtime
Fitting model: XGBoost_BAG_L1 … Training model for up to 486.77s of the
486.77s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.4219         = Validation score   (-mean_absolute_error)
        147.57s  = Training   runtime
        11.26s   = Validation runtime
Fitting model: NeuralNetTorch_BAG_L1 … Training model for up to 437.47s of the
437.46s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.596  = Validation score   (-mean_absolute_error)
        217.55s  = Training   runtime
        0.96s    = Validation runtime
Fitting model: LightGBMLarge_BAG_L1 … Training model for up to 361.36s of the
361.36s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -12.6342         = Validation score   (-mean_absolute_error)
```

```
        269.41s  = Training   runtime
        32.68s   = Validation runtime
Completed 3/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L2 … Training model for up to 360.0s of the
256.86s of remaining time.
        -11.3248         = Validation score   (-mean_absolute_error)
        0.41s    = Training   runtime
        0.0s     = Validation runtime
AutoGluon training complete, total runtime = 1543.57s … Best model:
"WeightedEnsemble_L2"
TabularPredictor saved. To load, use: predictor =
TabularPredictor.load("AutogluonModels/submission_96_C/")
Evaluation: mean_absolute_error on test data: -10.943448932340804
        Note: Scores are always higher_is_better. This metric score can be
multiplied by -1 to get the metric value.
Evaluations on test data:
{
    "mean_absolute_error": -10.943448932340804,
    "root_mean_squared_error": -31.11198877171017,
    "mean_squared_error": -967.9558453310196,
    "r2": 0.9230646421934396,
    "pearsonr": 0.9609647483772289,
    "median_absolute_error": -0.6210449779033658
}

Evaluation on test data:
-10.943448932340804
                     model  score_test  score_val  pred_time_test  pred_time_val
fit_time  pred_time_test_marginal  pred_time_val_marginal  fit_time_marginal
stack_level  can_infer  fit_order
0      WeightedEnsemble_L2  -10.943449 -11.324826       13.495278      70.277850
568.270702                0.003744                0.000570           0.409274
2       True         12
1        LightGBMXT_BAG_L1  -11.460927 -11.718563        3.735253      36.631079
80.900352               3.735253               36.631079          80.900352
1       True          3
2     LightGBMLarge_BAG_L1  -11.905294 -12.634178        9.238740      32.682299
269.408155                9.238740               32.682299         269.408155
1       True         11
3          LightGBM_BAG_L1  -12.290731 -13.213984        2.306371      13.760183
71.739522               2.306371               13.760183          71.739522
1       True          4
4    NeuralNetTorch_BAG_L1  -12.410340 -13.596046        0.517541       0.963902
217.552921                0.517541                0.963902         217.552921
1       True         10
5          CatBoost_BAG_L1  -12.841863 -12.783341        0.190703       0.262737
559.360764                0.190703                0.262737         559.360764
1       True          6
```

```
6           XGBoost_BAG_L1  -12.999348 -13.421861         2.820486       11.259993
147.566018                  2.820486                 11.259993         147.566018
1        True            9
7    NeuralNetFastAI_BAG_L1  -14.003227 -14.457019         1.219468        1.195696
93.040765                  1.219468                 1.195696          93.040765
1        True            8
8      ExtraTreesMSE_BAG_L1  -15.348385 -15.943328         0.335622        0.744498
1.023689                  0.335622                 0.744498          1.023689
1        True            7
9    RandomForestMSE_BAG_L1  -15.973298 -16.336346         0.291116        0.734572
4.864705                  0.291116                 0.734572          4.864705
1        True            5
10    KNeighborsDist_BAG_L1  -23.919332 -23.699493         0.013816        0.265059
0.024791                  0.013816                 0.265059          0.024791
1        True            2
11    KNeighborsUnif_BAG_L1  -24.102600 -23.647165         0.014048        2.424098
0.024903                  0.014048                 2.424098          0.024903
1        True            1
```




[14]:
```
# save leaderboards to csv
pd.concat(leaderboards).to_csv(f"leaderboards/{new_filename}.csv")
```

## 3 Submit

[15]:
```
import pandas as pd
import matplotlib.pyplot as plt

train_data_with_dates = TabularDataset('X_train_raw.csv')
train_data_with_dates["ds"] = pd.to_datetime(train_data_with_dates["ds"])

test_data = TabularDataset('X_test_raw.csv')
test_data["ds"] = pd.to_datetime(test_data["ds"])
#test_data
```

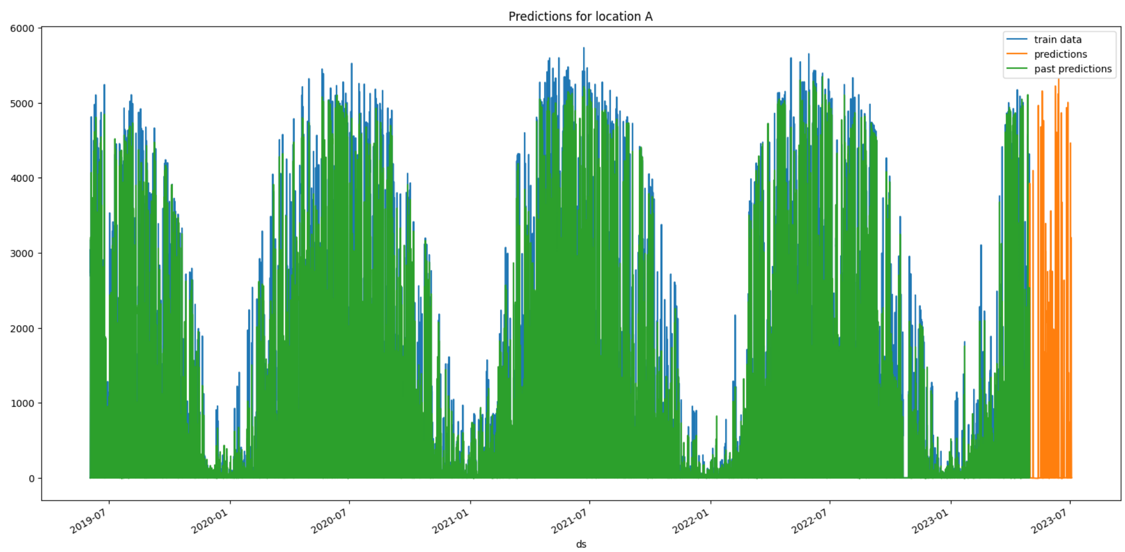
```
Loaded data from: X_train_raw.csv | Columns = 36 / 36 | Rows = 92945 -> 92945
Loaded data from: X_test_raw.csv | Columns = 35 / 35 | Rows = 4608 -> 4608
```

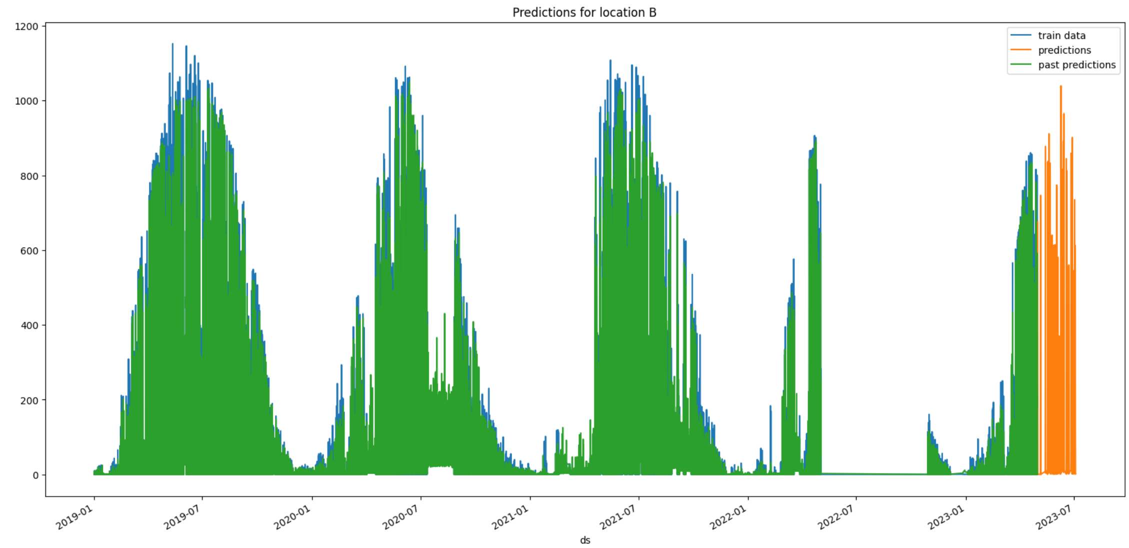
[16]:
```
test_ids = TabularDataset('test.csv')
test_ids["time"] = pd.to_datetime(test_ids["time"])
# merge test_data with test_ids
test_data_merged = pd.merge(test_data, test_ids, how="inner", right_on=["time",␣
↪"location"], left_on=["ds", "location"])

#test_data_merged
```

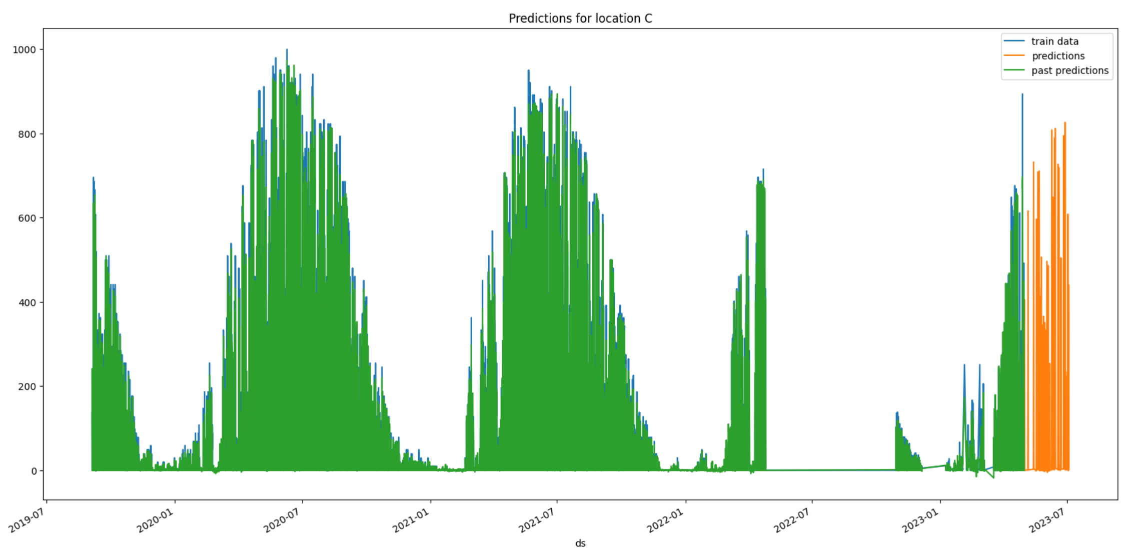
```
Loaded data from: test.csv | Columns = 4 / 4 | Rows = 2160 -> 2160
```

[17]:
```
# predict, grouped by location
predictions = []
location_map = {
    "A": 0,
    "B": 1,
    "C": 2
}
for loc, group in test_data.groupby('location'):
    i = location_map[loc]
    subset = test_data_merged[test_data_merged["location"] == loc].
↪reset_index(drop=True)
    #print(subset)
    pred = predictors[i].predict(subset)
    subset["prediction"] = pred
    predictions.append(subset)

    # get past predictions
    past_pred = predictors[i].
↪predict(train_data_with_dates[train_data_with_dates["location"] == loc])
    train_data_with_dates.loc[train_data_with_dates["location"] == loc,␣
↪"prediction"] = past_pred
```

[18]:
```
# plot predictions for location A, in addition to train data for A
for loc, idx in location_map.items():
    fig, ax = plt.subplots(figsize=(20, 10))
    # plot train data
    train_data_with_dates[train_data_with_dates["location"]==loc].plot(x='ds',␣
↪y='y', ax=ax, label="train data")

    # plot predictions
    predictions[idx].plot(x='ds', y='prediction', ax=ax, label="predictions")

    # plot past predictions
    train_data_with_dates[train_data_with_dates["location"]==loc].plot(x='ds',␣
↪y='prediction', ax=ax, label="past predictions")

    # title
    ax.set_title(f"Predictions for location {loc}")
```






[19]:
```python
# concatenate predictions
submissions_df = pd.concat(predictions)
submissions_df = submissions_df[["id", "prediction"]]
submissions_df
```

[19]:

| | id | prediction |
|---|---|---|
| 0 | 0 | -0.082104 |
| 1 | 1 | -0.000746 |
| 2 | 2 | -0.273771 |
| 3 | 3 | 62.498631 |

```
4       4  381.372986
..     …          …
715  2155   65.598755
716  2156   41.106895
717  2157   11.369844
718  2158    4.639547
719  2159    1.442424

[2160 rows x 2 columns]
```

[20]:

```
# Save the submission DataFrame to submissions folder, create new name based on
↪last submission, format is submission_<last_submission_number + 1>.csv

# Save the submission
print(f"Saving submission to submissions/{new_filename}.csv")
submissions_df.to_csv(os.path.join('submissions', f"{new_filename}.csv"),
↪index=False)
print("jall1a")
```

```
Saving submission to submissions/submission_96.csv
jall1a
```

[21]:

```
# save this running notebook
from IPython.display import display, Javascript
import time

# hei123

display(Javascript("IPython.notebook.save_checkpoint();"))

time.sleep(3)
```

```
<IPython.core.display.Javascript object>
```

[22]:

```
# save this notebook to submissions folder
import subprocess
import os
subprocess.run(["jupyter", "nbconvert", "--to", "pdf", "--output", os.path.
↪join('notebook_pdfs', f"{new_filename}.pdf"), "autogluon_each_location.
↪ipynb"])
```

```
[NbConvertApp] Converting notebook autogluon_each_location.ipynb to pdf
/opt/conda/lib/python3.10/site-packages/nbconvert/utils/pandoc.py:51:
RuntimeWarning: You are using an unsupported version of pandoc (2.9.2.1).
Your version must be at least (2.14.2) but less than (4.0.0).
Refer to https://pandoc.org/installing.html.
Continuing with doubts…
  check_pandoc_version()
[NbConvertApp] Support files will be in notebook_pdfs/submission_96_files/
```

```
[NbConvertApp] Making directory
./notebook_pdfs/submission_96_files/notebook_pdfs
[NbConvertApp] Writing 186797 bytes to notebook.tex
[NbConvertApp] Building PDF
[NbConvertApp] Running xelatex 3 times: ['xelatex', 'notebook.tex', '-quiet']
[NbConvertApp] Running bibtex 1 time: ['bibtex', 'notebook']
[NbConvertApp] WARNING | bibtex had problems, most likely because there were no
citations
[NbConvertApp] PDF successfully created
[NbConvertApp] Writing 2051301 bytes to notebook_pdfs/submission_96.pdf
```

[22]:
```
CompletedProcess(args=['jupyter', 'nbconvert', '--to', 'pdf', '--output',
'notebook_pdfs/submission_96.pdf', 'autogluon_each_location.ipynb'],
returncode=0)
```

[23]:
```python
# feature importance
location="A"
split_time = pd.Timestamp("2022-10-28 22:00:00")
estimated = train_data_with_dates[train_data_with_dates["ds"] >= split_time]
estimated = estimated[estimated["location"] == location]
predictors[0].feature_importance(feature_stage="original", data=estimated,␣
↪time_limit=60*10)
```

```
These features in provided data are not utilized by the predictor and will be
ignored: ['ds', 'elevation:m', 'location', 'prediction']
Computing feature importance via permutation shuffling for 32 features using
4392 rows with 10 shuffle sets… Time limit: 600s…
        2039.45s        = Expected runtime (203.95s per shuffle set)
        507.64s = Actual runtime (Completed 4 of 10 shuffle sets) (Early
stopping due to lack of time…)
```

[23]:

| | importance | stddev | p_value | n | \ |
|---|---|---|---|---|---|
| direct_rad_1h:J | 1.590809e+02 | 2.724940 | 6.925529e-07 | 4 | |
| clear_sky_energy_1h:J | 1.319484e+02 | 2.762976 | 1.265023e-06 | 4 | |
| clear_sky_rad:W | 1.296194e+02 | 2.668089 | 1.201645e-06 | 4 | |
| diffuse_rad_1h:J | 1.105292e+02 | 2.291321 | 1.227467e-06 | 4 | |
| diffuse_rad:W | 9.995892e+01 | 1.718785 | 7.005439e-07 | 4 | |
| direct_rad:W | 7.166362e+01 | 2.326761 | 4.713005e-06 | 4 | |
| sun_elevation:d | 6.769284e+01 | 1.824143 | 2.695351e-06 | 4 | |
| hour | 3.496914e+01 | 2.064970 | 2.829283e-05 | 4 | |
| effective_cloud_cover:p | 3.495665e+01 | 2.190691 | 3.380428e-05 | 4 | |
| sun_azimuth:d | 2.821977e+01 | 1.552842 | 2.290286e-05 | 4 | |
| is_in_shadow:idx | 2.238656e+01 | 0.852310 | 7.596526e-06 | 4 | |
| total_cloud_cover:p | 1.740795e+01 | 0.431494 | 2.097936e-06 | 4 | |
| snow_water:kgm2 | 1.651445e+01 | 0.938496 | 2.522293e-05 | 4 | |
| sfc_pressure:hPa | 1.475516e+01 | 2.170157 | 4.301319e-04 | 4 | |
| relative_humidity_1000hPa:p | 1.169462e+01 | 0.404922 | 5.715280e-06 | 4 | |
| msl_pressure:hPa | 1.079452e+01 | 1.642004 | 4.752177e-04 | 4 | |

| | | | | |
|---|---|---|---|---|
| visibility:m | 9.974443e+00 | 0.815795 | 7.495830e-05 | 4 |
| is_day:idx | 9.968553e+00 | 0.441618 | 1.196267e-05 | 4 |
| wind_speed_10m:ms | 9.415063e+00 | 0.597245 | 3.505644e-05 | 4 |
| t_1000hPa:K | 9.101788e+00 | 1.083050 | 2.293025e-04 | 4 |
| pressure_100m:hPa | 8.841513e+00 | 0.878574 | 1.340480e-04 | 4 |
| fresh_snow_6h:cm | 8.682340e+00 | 0.601390 | 4.560761e-05 | 4 |
| cloud_base_agl:m | 8.007614e+00 | 0.683189 | 8.504063e-05 | 4 |
| precip_type_5min:idx | 7.172939e+00 | 1.102105 | 4.895274e-04 | 4 |
| super_cooled_liquid_water:kgm2 | 7.148955e+00 | 0.938225 | 3.067983e-04 | 4 |
| ceiling_height_agl:m | 7.057437e+00 | 0.279091 | 8.512106e-06 | 4 |
| pressure_50m:hPa | 5.699006e+00 | 0.259217 | 1.294602e-05 | 4 |
| snow_depth:cm | 4.490204e+00 | 1.034865 | 1.609985e-03 | 4 |
| fresh_snow_3h:cm | 3.810029e+00 | 0.285142 | 5.748650e-05 | 4 |
| fresh_snow_1h:cm | 2.740081e+00 | 0.275603 | 1.389857e-04 | 4 |
| year | 1.369079e+00 | 0.303183 | 1.433291e-03 | 4 |
| is_estimated | -1.042267e-08 | 0.000000 | 5.000000e-01 | 4 |

| | p99_high | p99_low |
|---|---|---|
| direct_rad_1h:J | 1.670389e+02 | 1.511228e+02 |
| clear_sky_energy_1h:J | 1.400176e+02 | 1.238793e+02 |
| clear_sky_rad:W | 1.374114e+02 | 1.218274e+02 |
| diffuse_rad_1h:J | 1.172209e+02 | 1.038375e+02 |
| diffuse_rad:W | 1.049786e+02 | 9.493929e+01 |
| direct_rad:W | 7.845882e+01 | 6.486842e+01 |
| sun_elevation:d | 7.302017e+01 | 6.236551e+01 |
| hour | 4.099979e+01 | 2.893848e+01 |
| effective_cloud_cover:p | 4.135446e+01 | 2.855884e+01 |
| sun_azimuth:d | 3.275478e+01 | 2.368477e+01 |
| is_in_shadow:idx | 2.487569e+01 | 1.989743e+01 |
| total_cloud_cover:p | 1.866811e+01 | 1.614779e+01 |
| snow_water:kgm2 | 1.925528e+01 | 1.377361e+01 |
| sfc_pressure:hPa | 2.109300e+01 | 8.417311e+00 |
| relative_humidity_1000hPa:p | 1.287717e+01 | 1.051206e+01 |
| msl_pressure:hPa | 1.558992e+01 | 5.999120e+00 |
| visibility:m | 1.235694e+01 | 7.591951e+00 |
| is_day:idx | 1.125828e+01 | 8.678828e+00 |
| wind_speed_10m:ms | 1.115929e+01 | 7.670837e+00 |
| t_1000hPa:K | 1.226479e+01 | 5.938791e+00 |
| pressure_100m:hPa | 1.140735e+01 | 6.275677e+00 |
| fresh_snow_6h:cm | 1.043867e+01 | 6.926007e+00 |
| cloud_base_agl:m | 1.000284e+01 | 6.012391e+00 |
| precip_type_5min:idx | 1.039159e+01 | 3.954291e+00 |
| super_cooled_liquid_water:kgm2 | 9.889000e+00 | 4.408911e+00 |
| ceiling_height_agl:m | 7.872510e+00 | 6.242364e+00 |
| pressure_50m:hPa | 6.456038e+00 | 4.941975e+00 |
| snow_depth:cm | 7.512480e+00 | 1.467928e+00 |
| fresh_snow_3h:cm | 4.642774e+00 | 2.977284e+00 |

```
fresh_snow_1h:cm                3.544965e+00  1.935196e+00
year                            2.254510e+00  4.836481e-01
is_estimated                   -1.042267e-08 -1.042267e-08
```

[ ]:
```python
# feature importance
observed = train_data_with_dates[train_data_with_dates["ds"] < split_time]
observed = observed[observed["location"] == location]
predictors[0].feature_importance(feature_stage="original", data=observed,␣
 ↪time_limit=60*10)
```

```
These features in provided data are not utilized by the predictor and will be
ignored: ['ds', 'elevation:m', 'location', 'prediction']
Computing feature importance via permutation shuffling for 32 features using
5000 rows with 10 shuffle sets… Time limit: 600s…
        2174.69s        = Expected runtime (217.47s per shuffle set)
```

[ ]:
```python
display(Javascript("IPython.notebook.save_checkpoint();"))
time.sleep(3)

subprocess.run(["jupyter", "nbconvert", "--to", "pdf", "--output", os.path.
 ↪join('notebook_pdfs', f"{new_filename}_with_feature_importance.pdf"),␣
 ↪"autogluon_each_location.ipynb"])
```

[ ]:
```python
# import subprocess

# def execute_git_command(directory, command):
#     """Execute a Git command in the specified directory."""
#     try:
#         result = subprocess.check_output(['git', '-C', directory] + command,␣
 ↪stderr=subprocess.STDOUT)
#         return result.decode('utf-8').strip(), True
#     except subprocess.CalledProcessError as e:
#         print(f"Git command failed with message: {e.output.decode('utf-8').
 ↪strip()}")
#         return e.output.decode('utf-8').strip(), False

# git_repo_path = "."

# execute_git_command(git_repo_path, ['config', 'user.email',␣
 ↪'henrikskog01@gmail.com'])
# execute_git_command(git_repo_path, ['config', 'user.name', hello if hello is␣
 ↪not None else 'Henrik eller Jørgen'])

# branch_name = new_filename

# # add datetime to branch name
# branch_name += f"_{pd.Timestamp.now().strftime('%Y-%m-%d_%H-%M-%S')}"
```

```
# commit_msg = "run result"

# execute_git_command(git_repo_path, ['checkout', '-b',branch_name])

# # Navigate to your repo and commit changes
# execute_git_command(git_repo_path, ['add', '.'])
# execute_git_command(git_repo_path, ['commit', '-m',commit_msg])

# # Push to remote
# output, success = execute_git_command(git_repo_path, ['push',␣
↪'origin',branch_name])

# # If the push fails, try setting an upstream branch and push again
# if not success and 'upstream' in output:
#     print("Attempting to set upstream and push again...")
#     execute_git_command(git_repo_path, ['push', '--set-upstream',␣
↪'origin',branch_name])
#     execute_git_command(git_repo_path, ['push', 'origin', 'henrik_branch'])

# execute_git_command(git_repo_path, ['checkout', 'main'])
```